CONSTRUCTING LOW COST CORE-SATELLITE PORTFOLIOS WITH MULTIPLE RISK CONSTRAINTS: PRACTICAL APPLICATIONS TO ROBO ADVISING IN SOUTH AFRICA USING ACTIVE, PASSIVE AND SMART-BETA STRATEGIES

By

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Declaration

I, Jacques Smith, hereby declare that the work on which this thesis is based is my original work (except where acknowledgements indicate otherwise) and that neither the whole work nor any part of it has been, is being, or is to be submitted for another degree in this or any other University. I empower the University of Cape Town to reproduce this thesis for the purpose of research, either the whole or any portion of the contents, in any manner whatsoever.

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Abstract

Risk and tracking error budgeting was originally adopted by large institutional investors, including pension funds, plan sponsors, foundations, and endowments. More recently, risk and tracking error budgeting have gained popularity among financial advisors, multi-managers, fund of funds managers, high net worth individuals as well as retail investors. These techniques contribute to the portfolio optimisation process by limiting the extent to which a portfolio can deviate from its benchmark with regards to risk and tracking error.

This is an ambitious paper that attempts to determine the optimal strategy to practically implement risk and tracking error budgeting as a portfolio optimisation technique in South Africa. This study attempts to bridge the gap between active, passive, and smart-beta investment management styles by introducing a low-cost portfolio construction technique, for core-satellite portfolio management, which contributes to the risk and tracking error budgeting process. Core-satellite portfolios are designed to expose the portfolio to a low-cost primary *"core"* consisting of passive and enhanced index funds, thus systematic risk *"beta"*, limiting the tracking error of the portfolio. The secondary *"satellite"* component is allocated to active and smart-beta managers to exploit expected excess return *"alpha"*.

The primary aim of this research is to construct a rule-based product range of core-satellite portfolios called *"replica portfolios"*. The product range builds on the foundation of the Association for Savings & Investments South Africa (ASISA) framework. The study identifies three *"target portfolios"* from ASISA's framework, namely (1) High Risk: SA General Equity, (2) Medium Risk: SA Multi-Asset High Equity and (3) Low Risk: SA Multi-Asset Low Equity. Through this framework, active managers from each category are shortlisted using a Sharpe and Information Ratio filter. A secondary filtering technique, namely Returns Based Style Analysis (RBSA) is used to determine the style, R-squared and alpha-generating ability of active managers versus the passive asset classes and style indices they seek to replicate.

Applying Euler's theorem for homogenous functions, we decompose the risk of the core-satellite portfolio into the risk contributed by each of its components. The primary mandate of the core-satellite portfolios in the product range is to allocate risk and tracking error efficiently across several investment management styles and asset classes in order to maximise returns while remaining within the specified risk parameters.

The results highlighted that active managers, after fees, predominantly failed to outperform their benchmarks and passive building blocks, as identified through RBSA over the sample period (October 2009 – September 2019). However, only a small number of active managers generated superior risk-adjusted returns and were included in the core-satellite range of products. This study recommends to investors that they exploit the *"hot-hands effect"* by investing in specialised, benchmark agnostic active managers who consistently produce superior risk-adjusted returns. By blending active, passive and smart-beta strategies, investors are exposed to less total risk, less risk per holding and a lower tracking error. The three core-satellite portfolios developed in this study generated absolute and risk-adjusted returns that are more significant than their active and passive counterparts. Fee arbitrage was derived through the range of core-satellite products, resulting in tangible alpha over the sample period. The study encourages investors to use smart-beta strategies alongside active and passive funds since it improves Sharpe and Information ratios while enhancing the original portfolio's characteristics.

Keywords: Risk Budgeting · Tracking Error · Modern Portfolio Theory · Efficient Market Hypothesis · Core-Satellite Portfolio · Active Portfolio Management · Passive Portfolio Management · Smart-Beta · Returns Based Style Analysis · Robo-Advisor

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Soli Deo gloria

"If we knew what it was we were doing, it would not be called research, would it?"

- Albert Einstein

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List of Acronyms and Abbreviations

ASISA	The Association For Savings & Investments South Africa
AUM	Assets Under Management
BRICS	Brazil, Russia, Indian, China & South Africa
CAGR	Compound Annualised Growth Rate
CAPM	Capital Asset Pricing Model
CIS	Collective Investment Scheme
CML	Capital Market Line
EMH	Efficient Market Hypothesis
ER	Excess Return
ETF	Exchange Traded Fund
FOF	Fund of Funds
IFA	Independent Financial Advisor
IR	Information Ratio
JSE	Johannesburg Stock Exchange
LISP	Linked Investment Services Provider
RA	Robo-Advisor
RBSA	Returns Based Style Analysis
RFR	Risk Free Rate
S&P500	Standard & Poor's 500 Index
SAA	Strategic Asset Allocation
SR	Sharpe Ratio
TA	Technical Analysis
TAA	Tactical Asset Allocation
TE	Tracking Error
TIC	Total Investment Charge
US$	United States Dollar
ZAR	South African Rand

Chapter 1: Introduction

1.1 Research Background

"Perhaps the most important job of a financial advisor is to get their clients in the right place on the efficient frontier in their portfolios. But their No. 2 job, a very close second, is to create portfolios that their clients are comfortable with."

- Harry Markowitz

This research is undertaken from the viewpoint of a quantitative portfolio manager with potential applications to a Robo-advisor (RA) framework. The investment philosophy followed in this paper is inspired by John C. Bogle, who founded The Vanguard Group and the first index mutual fund in 1975, the Vanguard 500 Index Fund (VFINX). As of June 2019, the VFINX had US$492.2 billion in AUM, with an expense ratio of only 0.14 percent (Vanguard, 2019). Bogle's philosophy to successful investing over the long term, according to his original book *"Common Sense on Mutual Funds"* can be summarised according to these basic principles:

1. Identify low-cost investment strategies
2. Financial advice comes at a cost and investors should consider its added value
3. Past performance cannot be used to predict further performance in isolation
4. Past performance can, however, be used to assess risk and consistency
5. Construct a fund portfolio with a few assets and hold it indefinitely

Advisors, plan sponsors, foundations, endowments and retail investors are tasked with allocating capital most prudently while seeking to generate the highest risk-adjusted returns. To accomplish this objective, they need to determine the optimal blend between active, passive and style factors. These three methods of investment management have unique characteristics that render them advantageous to include in the greater portfolio context. By introducing real-world investment mandates obtained from the fund classification framework of The Association For Savings & Investments South Africa (ASISA), this analysis aims to construct a range of holistic, affordable and accessible portfolios that serve various risk profiles. The paper evaluates three-fund classification frameworks from ASISA as portfolio mandates called *"target portfolios"*. Using similar strategic asset allocations (SAA) as the *"target portfolios,* this study develops a product range of core-satellite portfolios called *"replica portfolios"* to mimic the SAA of South African Equity and Multi-Asset funds while reducing total cost. The *"replica portfolios*", discussed in Section 1.1.2, are designed to increase exposure to good tracking error when it is most desirable and to reduce tracking error when it is least desirable. The *"target portfolio"* mandates obtained from ASISA include:

1. SA General Equity
2. SA Multi-Asset High Equity, and
3. SA Multi-Asset Low Equity

This research intends to answer complex questions faced by investors such as, what is the ideal blend between active managers, passive managers and smart-beta managers in order to achieve the highest risk-adjusted return? How should investors manage active risk in the portfolio, particularly within the context of active risk, active return and tracking error?

1.1.1 Active vs Passive vs Smart-Beta Background

Active investors are always looking for opportunities to purchase mispriced securities that are trading at prices below their intrinsic value as determined by rigorous fundamental analysis. Active investors aim to generate profits by selling securities once they reach their actual intrinsic value. Sharpe (1991) points out than an active investor's portfolio will differ from that of the passive investor almost all of the time. Active investors act on the perception of mispricing, and these perceptions frequently change as market conditions change. Active managers, therefore, trade more frequently compared to passive managers, hence the term *"active"*, which results in higher fees. Active investing can be considered a zero-sum-game (Sharpe, 1991). On average, actively managed mutual funds underperform after accounting for expense ratios (Fama & French, 2010). Fama and French (2010) further note that active managers with enough skill to generate positive returns net of fees are outnumbered by active managers who fail to generate positive net returns after accounting for expense ratios.

On the opposite side of the spectrum is the passive investor. Sharpe (1991) describes the passive investor as one that invests in every security that forms part of the market portfolio or benchmark, with each holding representing the exact weight as in the market. Passive investing, through Exchange Traded Funds (ETFs) and low-cost index funds, have grown significantly over the past several decades. Furthermore, passive investing has led to significant cost savings. Vanguard, one of the industry leaders in the passive investment management environment has approximately US$5.2 trillion in global assets under management, as of January 31, 2019, with a range of 415 low-cost traditional funds and ETFs. Boston Consulting Group (2019) reports that globally active managed assets lost US$1 trillion in AUM in 2018. Today, actively managed assets account for just US$1 out of every US$3 of global AUM, compared to US$1 out of every US$2 of AUM in 2003 (Boston Consulting Group, 2019).

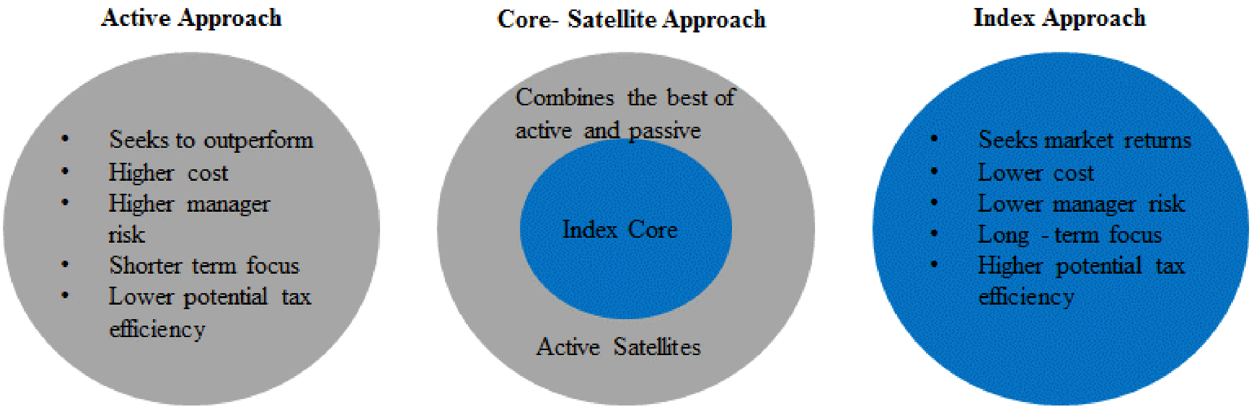
Active and passive investment styles are clearly on opposite ends of the spectrum when it comes to allocating capital. However, the latest addition to investment styles, called fundamental indexing, style factors or smart-beta falls somewhere in the middle of active and passive investing. Factor investing, or smart-beta investing as a style has been hugely successful over the last decade, with the most substantial part of smart-beta AUM growth derived by ETF strategies. According to Morningstar (2017), smart-beta AUM for public vehicles, mutual funds and ETFs increased from US$280 billion in 2012 to US$999 billion at the end of 2017. Moreover, the most significant statistics are found in the growth of the number of smart-beta products available to investors. During 2013, 66 new smart-beta ETFs were launched to the global market compared to 302 new smart-beta ETFs that were launched in 2017 (Morningstar, 2017). The success of smart-beta investing can be attributed to its ability to bridge the gap between active and passive investing. Arnott, Hsu and Moore (2005) found that fundamentally based market portfolios that were constructed using metrics other than market capitalisation weighting, including revenue, dividends and book value outperformed the S&P500 Index by an average of 1.97 percent per annum over a 43-year time horizon.

1.1.2 Core-Satellite Portfolio Background

Treynor and Black (1973) revolutionised the idea of portfolio selection when they proposed a model to construct an optimal portfolio under the assumption that investors consider markets to be efficient and securities priced efficiently. However, these investors believe they have sufficient information at their disposal to predict the expected returns or abnormal performance *"alpha"* of some of the securities. This model, formally known as the Treynor Black Model (TBM) states that the optimal portfolio must consist of a blend between active and passive components. A specified market index is used as the efficient *"passive"* primary component of the portfolio, and these securities are not analysed as they are assumed to be efficient and therefore correctly priced. The secondary *"active"* component of the portfolio consists of securities that are covered by analysts of a portfolio management firm and are deemed inefficient as they are not included in the efficient market index. The TBM obtains the optimal risky portfolio by blending the securities that are deemed inefficient *"active alpha"* with the efficient market index *"passive beta"*. The success of the TBM is a consequence of its simplicity as it does not require plentiful information, and it is designed to convey the solution for the optimal portfolio in a simple algebraic formula. This optimal portfolio would be exposed to securities that exhibit forecasted outperformance $(Alpha > 0)$, with zero, or less exposure to securities that exhibit forecasted underperformance $(Alpha < 0)$. Optimal allocations in each security are proportional to its expected alpha.

The desire to improve investment efficiency in recent years has given rise to a core-satellite approach to portfolio management (Amenc, Malaise & Martellini, 2004). Core-satellite portfolios can be broken down to a *"core"* component which is usually passive and is managed by a mainstream manager and a secondary *"satellite"* active component, which is allocated to less efficient markets and asset classes as expressed by **Figure 1.1**. The idea of the passively managed core component of the portfolio is to control manager specific risk and to improving the overall efficiency of the portfolio and its ability to outperform its benchmark by limiting costs. The secondary component of the portfolio, which is allocated to active and smart-beta managers, aims to provide additional diversification and to generate outperformance during market downturns.

Figure 1.1: The Core-Satellite Portfolio Combines the Benefits of Passive and Active Management



Source: Authors depiction & Vanguard (2017)

Core-satellite portfolio management has proven to be a cost-efficient way to control the relative risk, also known as tracking error risk within the consolidated portfolio (Amenc, Malaise & Martellini, 2004). Risk and tracking error budgeting should be regarded as a double-edged sword which can prove to be beneficial or disastrous in the portfolio construction context.

There is good tracking error, which refers to the outperformance of the portfolio with regards to its benchmark and bad tracking error which refers to the underperformance of the portfolio to the benchmark (Amenc, Malaise & Martellini, 2004). Advisors, plan sponsors, foundations, endowments and retail investors would ideally position their portfolios to be only exposed to good tracking error. Vanguard (2017) mentions that many globally renowned financial planning practises have embraced and implemented core-satellite portfolio management techniques into their business models.

1.1.3 Robo-Advisor Background

This research aims to propose potential applications of a rules-based Robo-advisor (RA), making affordable portfolio optimization accessible to all types of investors. The term Robo-advisor has become a well-known buzzword with promising growth prospects in store for their services. Beketov *et al*. (2018) describe RAs as an *"automated investment platform that uses quantitative algorithms and techniques to manage portfolios and is accessible to clients online".* A recent study conducted by Deloitte (2018) indicated that South Africans are open to using automated financial advice, particularly individuals between the ages of 34-44 and the individuals most interested are those who earn less than R750 000 per annum. Van Rooij, Lusardi and Alessie (2011) mention that the complexity of financial decision that individuals face has increased to unprecedented levels in recent times. One particular shortcoming tends to be that individuals are short-sighted when faced with financial decisions which may lead them to be ill-prepared for retirement. Calvet, Campbell and Sodini (2007) find that low levels of income, wealth and financial education predicts nonparticipation in financial markets, particularly equity markets, which leads to lower levels of portfolio diversification. Finally, Cocco, Gomes, and Maenhout (2005) evaluate the importance of portfolio and asset class choice over the life cycle of the investor. They find that nonparticipation in equity markets contribute to a significant source of welfare loss throughout the individual's life compared to those who do participate in equity markets. Moreover, they support the popular notion that the portfolio's share invested in equities should roughly decrease with age.

1.2 Research Problem Statement

The South African financial market offer investors infinite opportunities to allocate capital most efficiently. The concept widely known as modern portfolio theory initially described by Markowitz (1952), stipulates that investors are typically risk-averse and should, therefore, prefer to be invested in the portfolio with the lowest level of risk for a given level of expected return. Applying the concept of modern portfolio theory in practice, however, is more a science than an art. Investors who wish to allocate capital in a CIS such as a unit trust, or ETF are spoilt for choice. It is no easy task to determine which CIS is most suited for advisors, plan sponsors, foundations, endowments, retail investors and most importantly, unsophisticated investors.

The Association For Savings & Investments South Africa (ASISA) was launched in October 2008 to improve the savings and investment culture as well as make financial services more accessible and interpretable to South African investors. As of March 2019, there were 1599 unit trust funds available in South Africa. ETFSA indicate that investors can invest in up to 77 ETFs in South Africa. Comparing these numbers to the number of listed companies on the Johannesburg Stock Exchange (JSE), the JSE reported 360 listed companies as at June 2019. This data suggests that it is far more complicated and challenging for investors to construct a portfolio consisting of CISs, compared to a portfolio consisting only of listed securities.

ASISA (2018) provides a basic framework to help investors choose as to which CIS to include in their portfolio. Formally known as the *"ASISA standard for fund classification for South African-regulated collective investment portfolios",* aims to provide *"a framework within which portfolios with comparable investment objectives and investment universes are grouped".* The framework is an essential tool that enables investors to match their risk profile, risk tolerance and return objective to the CIS funds that are most suited to achieve their investment goals. However, with 1599-unit trust funds available, we believe a more straightforward approach can be proposed to constructing portfolios in South Africa.

The research problem statement this paper sets out to address is whether specific ASISA fund categories within the classification can be allocated towards standardised risk profiles, called *"target portfolios".* This research attempts to determine the optimal blend between active managers *(unit trusts),* passive managers *(ETFs and index funds)* and smart-beta funds in order to achieve the highest risk-adjusted return, while remaining within the risk profiles and SAA restrictions of the ASISA fund classification framework. The desired outcome of this research is the development of a product range of low-cost core-satellite portfolios that replicate the

SAA of the *"target portfolios"* within ASISA's framework. Investors can use the *"replica portfolios"* within the product range throughout their entire investment careers as they encompass high, medium and low-risk portfolios.

The research implements multidimensional risk and tracking error budgeting. These techniques contribute to the portfolio optimisation process by limiting the extent to which a portfolio can deviate from its benchmark with regards to risk and tracking error. It enables investors to gain maximum exposure to expected alpha *"excess return"*, while not exceeding a predetermined tracking error, total risk budget, and risk budget per holding. Applying Euler's theorem for homogenous functions, we decompose the risk of the core-satellite portfolio into the risk contributed by each of its components. The primary mandate of the core-satellite portfolios in the product range is to allocate risk and tracking error efficiently across several investment management styles and asset classes in order to maximise returns while remaining within the specified risk parameters. Euler's theorem provides a general method for additively decomposing risk into individual asset contributions and thus determine the optimal core component of each portfolio depending on its risk profile. When does it serve investors to be exposed to *"good"* tracking error, and what are the risks and costs associated with it?

Finally, the study evaluates the quantitative methodologies that can be found in third and fourth generation Robo-advisors. These RAs are superior when compared with first- and second-generation RAs since they use proven quantitative methods and algorithms to develop and rebalance portfolios. In addition to providing sound financial advice to clients, these RAs perform as automated portfolio managers. The study wishes to propose additional, more robust methods that can be incorporated by the next generation of RAs to provide an optimised version of standardised, prudent and calculated financial advice to both sophisticated and unsophisticated investors. This will reduce the overall cost of investing, while increasing the risk-adjusted returns of portfolios with several risk profiles.

1.3 Motivation

"Portfolio theory, as used by most financial planners, recommends that you diversify with a balance of stocks and bonds and cash that's suitable to your risk tolerance."

- Harry Markowitz

The motivation behind this research is threefold:

First and foremost, to the best knowledge of the author in the time of writing, the majority of prior research and literature on the subject of portfolio optimisation has been conducted using data from developed markets, with little attention being focused to emerging markets and specifically the South African market. The concept of mean-variance optimisation, developed initially by Markowitz (1959), is regarded as the cornerstone of modern finance theory.

Jorion (1992) applies portfolio optimisation in practice to the problem of the optimal portfolio from the context of a US investor. Mean-variance analysis, as proposed by Markowitz (1959) assumes that investors prefer portfolios with higher expected return in relation to risk. The classical approach to mean-variance optimisation can adequately integrate portfolio and return objectives with policy and risk constraints. Additionally, mean-variance optimisation's ability to incorporate numerous client constraints make it a remarkably flexible and useful tool in the portfolio construction context. The optimal portfolio Jorion (1992) constructed used data from seven major developed government markets, with returns being measured in US$. It was highlighted that when investors have more assets at their disposal to choose from, a more widely diversified portfolio cannot generate returns less than a portfolio of fewer assets (Jorion, 1992). Studies on portfolio optimisation in developed markets, with particular focus on tracking error and asset allocation, conducted by Ammann and Zimmermann (2001) in which they investigate the relationship between statistical measures of tracking error and asset allocation restrictions within the portfolio. This research addressed numerous issues in practical asset management.

The idea of core-satellite portfolio management as a portfolio optimisation technique has been explored by Waring *et al*. (2000) in which they present a methodology that solves structural problems involved when including active managers in the consolidated portfolio. They address how active risk, introduced to the portfolio through active managers, can be controlled as well as how active and passive managers should be held as a structure within the portfolio. Waring *et al*. (2000) suggest that investors with higher active risk budgets allocate a large portion of their capital to active managers while investors with lower active risk budgets allocate the majority of their capital to index and enhanced index funds. Markowitz (1959), Jorion (1992), Ammann and Zimmermann (2001) and Waring *et al*. (2000) addressed numerous issues in the portfolio optimisation debate. However, their data was restricted to developed markets only. Later studies by Amenc, Malaise and Martellini (2004) introduced a dynamic core-satellite approach to managing relative risk in the portfolio. Their results indicated that investors would want to increase their allocations to the satellite *"active"* component of the portfolio when it has outperformed the benchmark. Their study did however, not include useful data to practically implement the dynamic core-satellite approach, which is something the author wishes to explore in this paper.

Secondly, with the literature in mind regarding portfolio optimisation the author intends to explore and critically evaluate South African literature and its findings on active portfolio management, passive portfolio management and factor investing, or so-called *"smart beta"*. The outcome and conclusions of the analysis of the South African unit trust industry are inconclusive (Bertolis & Hayes, 2014). With regards to the success of passive and smart beta investment strategies, the findings of Daswa (2016) highlighted that ETF's across all markets failed to replicate their respective benchmark indices successfully. He further noted that the tracking error of emerging market ETF strategies was higher compared to ETF strategies from developed markets. These findings will be evaluated in order to assess the advantages of including passive investment management techniques within the portfolio optimisation process. Fundamental Indexation, factor investing, or so called "smart-beta" investment management techniques will be explored, particularly in light of the South African market.

Research by Duyvené de Wit and Polakow (2017) explore whether the sources of value-add *"alpha"* of South African active fund managers are accessible in cheaper formats such as smart-beta products. Their findings mention five broad predictions around the future of active fund management in South Africa. The most striking prediction is that there will be an emergence of more intellectual and smarter investment products available to South African investors. It will include a *"new flavour"* of active managers that use financial engineering to generate exposure to non-replicable alpha. This will result in investment skills being devoted to generating alpha free of benchmark impositions, forcing active managers who are deeply fundamental and research motivated in their investment approach to adopt a quantitative *"flavour"* to stay competitive (Duyvené de Wit & Polakow, 2017).

Finally, having worked in the investment management industry in South Africa and reporting to portfolio managers, financial planners, advisors and investment consultants it was apparent that the number of financial products at their disposal was limitless. These products were sophisticated and targeted relative returns, while giving little consideration to the risks and costs associated with them. It was further evident that wealthy, sophisticated investors with larger balance sheets were able to pay considerably more to receive prudent investment advice. In comparison, unsophisticated investors did not receive equal opportunities which relate to the findings of Calvet, Campbell and Sodini (2007) that low levels of income, wealth and education lead to nonparticipation in financial markets as well as lower levels of diversification within their consolidated portfolios.

To summarise, the motivation of this research is to contribute to the investment and savings culture in South Africa. By developing a product range of low-cost core-satellite portfolios, underpinned by several robust quantitative techniques. The product range is designed to potentially be implemented by an RA platform that uses algorithms and big data to propose the optimal risky portfolio consisting of active, passive and smart-beta strategies.

1.4 Research Aims

Firstly, this study aims to identify investment mandates from the fund classification framework of The Association For Savings & Investments South Africa (ASISA) and determine their strategic asset allocation bounds and restrictions.

The study intends to replicate, as close as possible the asset allocation and risk profiles of the these *"target portfolios"* by developing a product range of low-cost core-satellite portfolios called *"replica portfolios"*. The portfolios are designed to expose the investor to a low-cost primary *"core"* consisting of passive and enhanced index funds, thus systematic risk *"beta"*, limiting the tracking error of the portfolio. The secondary *"satellite"* component of the portfolio is allocated to active and smart-beta managers to exploit expected excess return *"alpha"*.

The study sets out to evaluate the state of market efficiency of developed stock markets as well as emerging stock markets. We are particularly interested in the efficiency of the South African stock market and determined to identify the most appropriate investment stagey to use during various states of market efficiency. Therefore, the research critically evaluates literature surrounding active, passive and smart-beta management, locally and internationally.

The research intends to evaluate several methodological frameworks to identify active managers, including Sharpe and Information Ratios, as well as Returns Based Style Analysis (RBSA), introduced initially by Sharpe (1988, 1992). Finally, the research wishes to explore multidimensional risk and tracking error budgeting techniques that can be practically implemented to enhance the core-satellite portfolio construction approach. We wish to determine whether this technique of portfolio optimisation can increase risk-adjusted returns for South African portfolios.

1.5 Research Structure

Chapter 1 – Introduction: This chapter includes the research background, research problem statement, the motivation for undertaking the research as well as the aims the author wish to achieve with the research. This chapter is paramount as to why investors should use multiple investment strategies within their portfolios.

Chapter 2 – Literature Review: This chapter sets out to discuss the evolution and literature of portfolio management as it is known today. The chapter evaluates fundamental principles including Modern Portfolio Theory, the efficient frontier along with the minimum variance portfolio and tangency portfolio. This chapter is extended to evaluate the theory of market efficiency and random walk theory, internationally and within South Africa. The literature review covers asset pricing models and the validity of conducting fundamental and technical analysis when analysing securities. We critically evaluate literature and finding surrounding active, passive and smart-beta investment styles in developed and emerging stock markets and determine the optimal strategy to generate superior returns in several states of market efficiencies. We present a famous case study that attempts to give the reader some insight and potential real-life applications of the theory of active versus passive management we have discussed so far. This chapter evaluates literature that introduces robust risk and tracking error budgeting and how it can be combined within the core-satellite portfolio. The final discussion covered in chapter 2 includes Robo-advisors and the cutting-edge quantitative methods they use to construct and manage portfolios.

Chapter 3 – Methodology: This chapter of the research sets out to discuss several mythological frameworks. These methodologies including:

1. Risk Budgeting, Euler's Theorem and Risk Decompositions
2. Tracking Error and Tracking Error Budgeting
3. Information Ratio
4. Core-Satellite Portfolios, Optimal Manager Allocation Mechanics and Fee Arbitrage
5. Returns Based Style Analysis

Each of the above methods will be covered in detail, along with their advantages and disadvantages. The desired outcome is to incorporate all of the above when constructing a product range of low-cost core-satellite portfolios. The desired outcome is to propose the portfolio construction technique developed in this research to Robo-advisors.

Chapter 4 – Data: Covers the classification framework used throughout this study. This chapter discusses ASISA's asset allocation framework for classifying South African unit trusts along with the risk classification framework suggested by PlexCrown (2019). This chapter aims to inform the reader about the sources used to obtain the data, data periods and data types.

Chapter 5 – Data Analysis, Results Discussion and Portfolio Construction: This chapter implements the methodologies set out in chapter 3 and develops a product range of low-cost core-satellite portfolios. The *"replica portfolios"* are constructing using the following steps:

1. Apply Sharpe and Information Ratio filters to shortlist active managers
2. Returns Based Style Analysis to select the best active managers
3. Core-satellite portfolios with multidimensional risk and tracking error budgets

Chapter 6 – Conclusions, Recommendations and Limitations: The final chapter sets out to make concluding comments and to summarise the research findings. This chapter is aimed at providing the reader with a consolidated synopsis. Research limitations are discussed along with recommendations for further research in the field of finance, financial planning, behavioural finance as well as computer science.

Chapter 2: Literature Review

2.1 Modern Portfolio Theory

Modern portfolio theory can be considered the cornerstone of the study of portfolio management from a scientific perspective, incorporating both economic and quantitative methodologies. Harry Markowitz is credited as having founded Modern Portfolio Theory (MPT) with his seminal paper *"Portfolio Selection"*. Markowitz (1952) gives a clear and mathematically precise definition for risk and more importantly, an empirical justification for the value of diversification as an investment strategy within the portfolio construction context.

Markowitz (1952) argues that rational investors are typically risk-averse and should, therefore, prefer to invest in the portfolio with the lowest level of risk for a given level of expected return. Therefore, investors should consider both returns as well as the variance of returns when allocating capital to asset classes or securities. The return or expected return is simply a measure of performance, while the variance of returns is a measure of the inherent risk of the asset class or security.

Risk aversion, for rational investors, can be expressed as follows:

- When investors compare two stocks with similar return or expected return profiles, the one with the smaller variance (risk) is preferable.

- When investors compare two stocks with the same variance (risk), the one with the highest return or expected return is preferable.

Applying the concept of modern portfolio theory in practice, however, is more a science than an art. Suppose the comparison is not as simple as the one highlighted above and security or asset class A demonstrates both higher returns or expected return characteristics as well as a higher variance compared to security or asset class B.

The investor now has to make their decision whether to invest in A or B based on the amount of risk they are willing to take, also known as their risk tolerance. The investor has to determine whether the additional return from investing in security A is worth the additional risk inherent in security A. Markowitz (1952) primary contribution to MPT was defining the performance of an investment portfolio by incorporating the return and variance of securities.

Equation 2.1 represents the return for stock i from a time interval $(t-1, t)$:

$$R_i\,(t) = \frac{P_i\,(t) - P_i\,(t-1)}{P_i\,(t-1)} \tag{2.1}$$

Where

$P_i\,(t)$ = the price of stock i at time t.

Note: this is a random variable, and we donate the expected value by:

$$\mu_i(t) = E\,[R_i\,(t)] \tag{2.2}$$

Considering a portfolio that consists of several securities. The expected return for the portfolio can be expressed as:

$$\mu_P = E\left[\sum_{i=1}^{N} x_i\,R_i\right] = \sum_{i=1}^{N} x_i\;\mu_i = \mathrm{x}^T\mu \tag{2.3}$$

Where

x_i = represents the percentage of the investment that is invested in stock i

The variance of a stock or asset is a measure of how much the price changes or fluctuates. For an individual stock, the variance in return is expressed as:

$$Variance\,(R_i) = E\,[(R_i - \mu_i)^2]\,, \tag{2.4}$$

The covariance in return for a two-stock portfolio can be expressed with the following equation:

$$\sigma_{ij} = E\left[(R_i - \mu_i)(R_j - \mu_j)\right] \tag{2.5}$$

The variance in return of a portfolio consisting of several stocks, assets or funds can be expressed as:

$$Variance\ (R_P) = \sigma_P^2 = \sum_{i,j} x_i\, \sigma_{ij} x_j = \mathrm{x}^T \textstyle\sum \mathrm{x} \tag{2.6}$$

The portfolio that offers the highest possible return for the given level of variance *(risk)* is considered to be efficient. The portfolio optimisation problem can be expressed as:

$$Minimise \quad \frac{1}{2}\mathrm{x}^T \textstyle\sum \mathrm{x} - \frac{1}{\lambda}\mathrm{x}^T \mu$$

Subject to:

$$\sum_i x_i = 1 \tag{2.7}$$

$$x_i \geq 0 \text{ for all } i$$

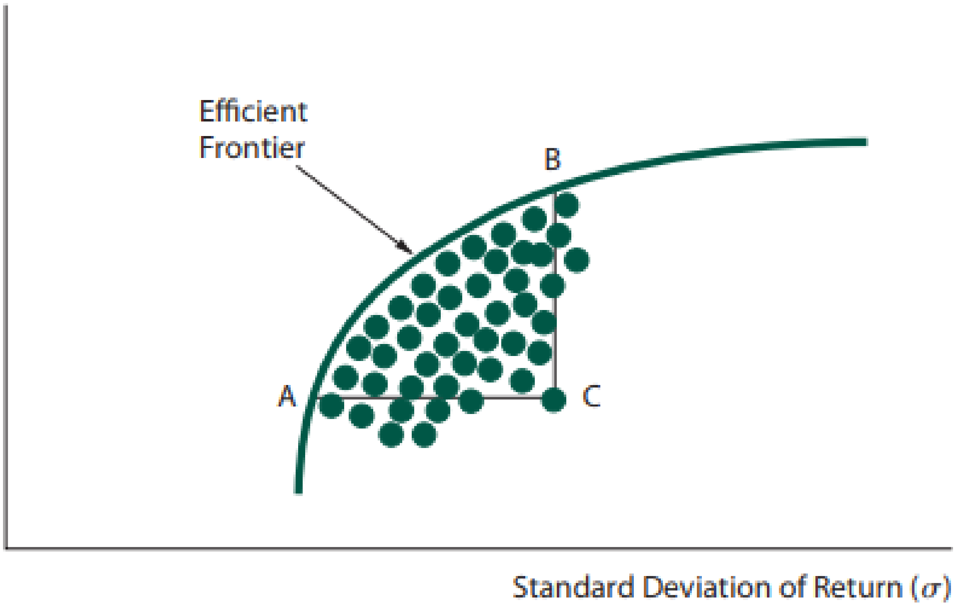
In equation 2.7, risk should be small, while returns should be large. The parameter $\lambda > 0$ multiplying the second term is a measure of risk tolerance. If λ is small or close to zero, the second term dominates and we can conclude that the investor prefers return over risk and therefore has a high-risk tolerance or is risk-tolerant. In contrast, if we find that λ is large, the second term receives less weight in the portfolio construction process, and we can conclude that the investor is risk-averse and favours low risk over return. MPT is primarily based on the theory of efficient markets. If the theory of efficient markets is accurate, then no active portfolio manager should be able to generate returns better than that of the market. We aim to explore this theory further in order to justify the inclusion of active portfolio managers within the portfolio construction context. Considering the literature around MPT, this study will evaluate the way investors evaluate risk and returns. Furthermore, in the light of allocating capital in financial markets and the potential inclusion of active portfolio managers, we will evaluate empirical evidence to determine whether markets can be regarded as efficient.

2.2 Asset Prices Under Conditions of Risk

2.2.1 The Efficient Frontier

Markowitz (1959), introduces the efficient frontier which aims to solve the optimal level of portfolio diversification in maximising returns while minimising risk. At its core, the efficient frontier is a graph that represents the relationship between return and risk for a given set of portfolios. Specifically, *"the efficient frontier represents that set of portfolios that has the maximum rate of return for every given level of risk or the minimum risk for every level of return".* The portfolio that lies on the efficient frontier must maximise return for a given level of risk. **Figure 2.1** illustrates the efficient frontier for theoretical alternative portfolios:

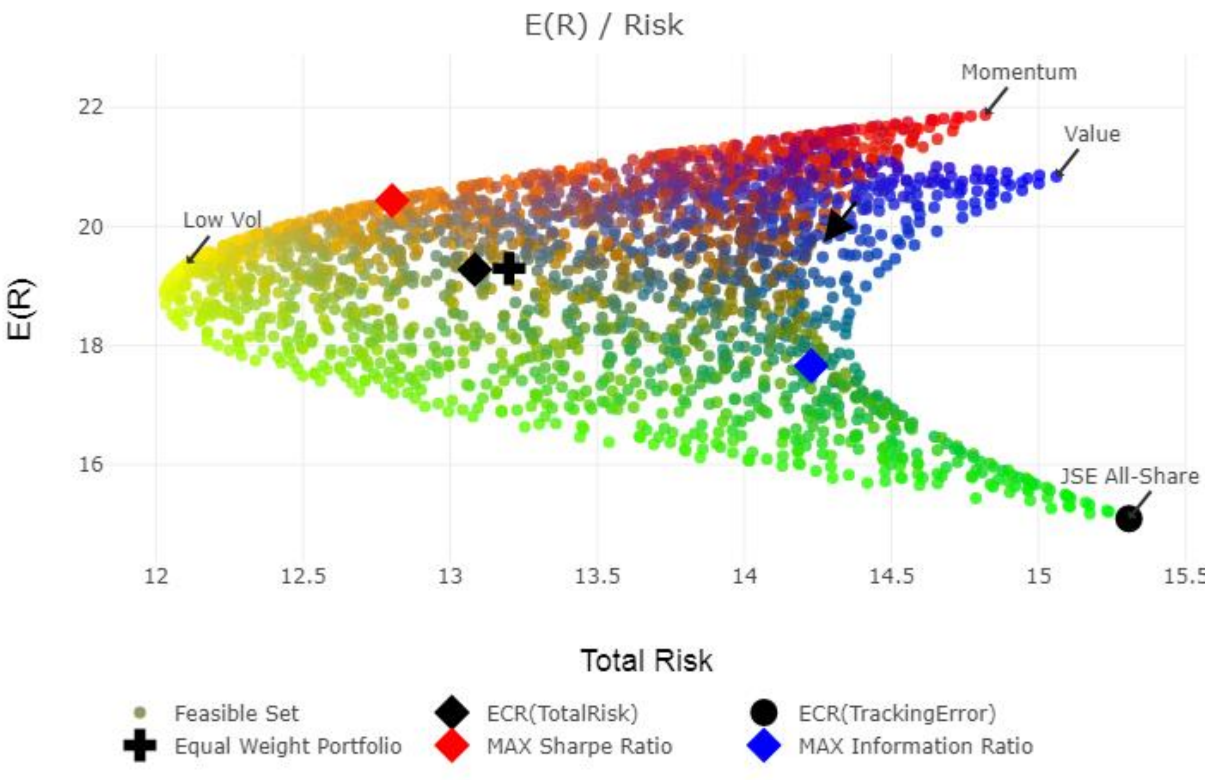
Figure 2.1: The Efficient Frontier for Theoretical Alternative Portfolios



Source: Reilly and Brown (2012: 189)

From **Figure 2.1** we conclude that every portfolio that lies on the efficient frontier either exhibits a higher rate of return of equal levels of risk or lower levels of risk for an equal rate of return that another portfolio that plots below the efficient frontier (Reilly & Brown, 2012). Portfolio A > C because Portfolio A has a similar return profile compared to Portfolio C, however Portfolio A has substantially less risk. Similarly, we find that Portfolio B > Portfolio C because it has a similar risk profile, but Portfolio B has a higher expected rate of return. The efficient frontier consists of portfolios of assets rather than individual securities due to the assumption of diversification that exists between uncorrelated assets. At the extreme ends of the efficient frontier, we find the only exceptions which represent the asset with the highest expected return and the asset with the lowest level of risk. A practical application to the efficient frontier is illustrated by **Figure 2.2**:

Figure 2.2: The Efficient Frontier for Practical Alternative Portfolios



Source: Authors depiction using A-Dex Prism

This practical illustration of the efficient frontier was derived by including four building blocks that exist in South Africa and include (1) JSE All-Share Index, (2) Momentum Style Factor, (3) Value Style Factor and (4) Low Volatility Style Factor. The benchmark portfolio, in this case, is the JSE All-Share Index. **Figure 2.2** illustrates a a representative sample of the feasible set which includes 2000 sample portfolios of all possible blends of the selected building blocks for the period 2003 - 2018 *(Index and Styles)* where each is presented in Expected Return, Total Risk *(measured by annualised standard deviation of returns)* and TE *(return differentials between a portfolio of assets and a defined benchmark*). Here we notice that the Momentum Style Factor Portfolio (*in red)* generated an annualised return of 21.88% with a total risk of 14.82% compared to the JSE All-Share Index (*in black)* that generated an annualised return of 15.09% with a total risk of 15.31%. We can therefore conclude that the Momentum Style Factor Portfolio is superior to the JSE All-Share Index according to the efficient frontier theory.

When investors move from the bottom left of the efficient frontier upwards and right, the risk (measured by the annualised standard deviation of returns) as well as the returns increase. If we analyse **Figure 2.2,** we notice that for every portfolio or feasible set that offers a level of expected return, there is another portfolio that offers the same level of expected return while incurring a lower level of risk. Portfolios that plot on the efficient frontier provides investors the maximum expected return for a given level of risk.

Markowitz (1991) argues that the goal for investors is to identify and invest in the portfolio that matches their risk tolerance while avoiding or limiting the amount of capital allocated to inefficient portfolios. Allocation of capital towards an inefficient portfolio would expose the investor to a certain level of risk without acquiring the corresponding optimal level of return. This leads us to the next question; how would investors target a point along the efficient frontier that satisfies their attitude towards risk?

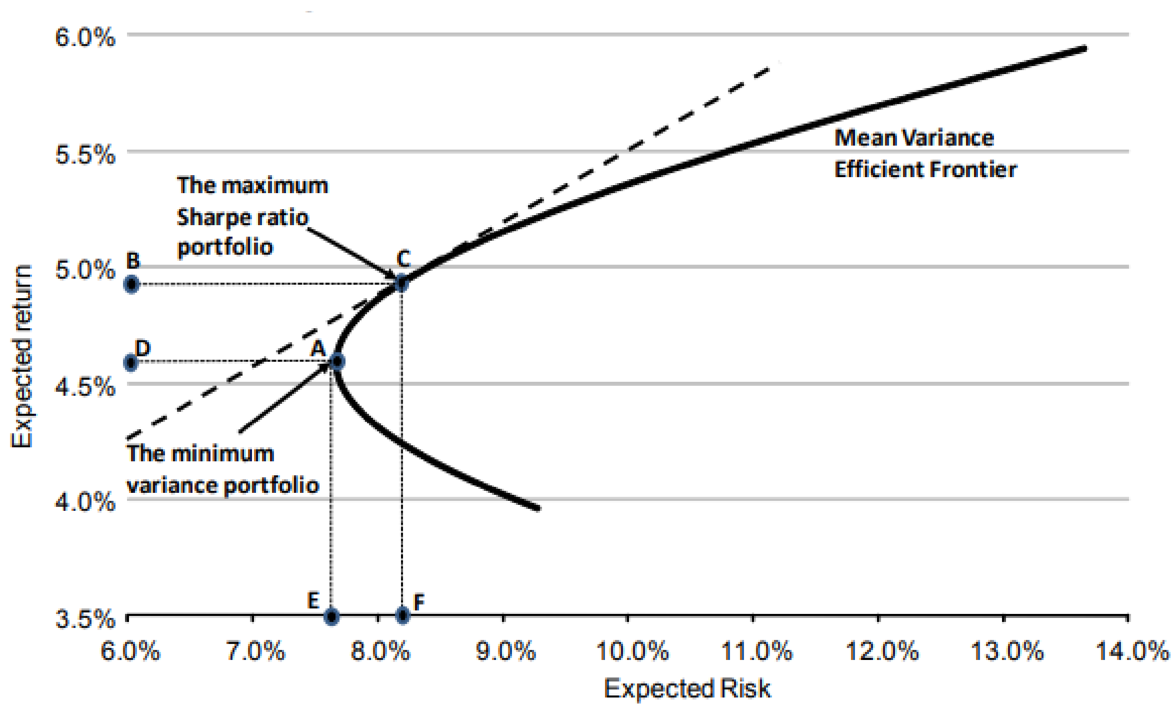
2.2.2 Minimum Variance Portfolio and Tangency Portfolio

Consider a group of investors who wish to invest in the portfolio that offer the least amount of risk, i.e. completely risk-averse and wish to invest without incurring risk and are agnostic about the potential expected return implications of the portfolio. These investors would ideally identify portfolios or feasible sets that plot on the efficient frontier with the least amount of risk as measured by standard deviation, implying the minimum variance.

This is what is called the minimum-variance portfolio, the portfolio at the left-most tip if the efficient frontier that holds independent security or asset class weights of the forecasted expected returns of those securities or asset class. Thus, the minimum-variance portfolio is designed to minimise risk without an explicit expected return estimation (Clarke, de Silva & Thorley, 2006).

Figure 2.3 illustrates the minimum-variance portfolio for a feasible set of theoretical portfolios as point A on the mean-variance efficient frontier. One important conclusion derived by Clarke, de Silva and Thorley (2006) regarding the use of minimum variance portfolios is that these portfolios have the potential to add value over the market capitalisation-weighted benchmark. We wish to explore this concept in the subsequent chapter in light of the findings made by Clare, Motson and Thomas (2013).

Figure 2.3: The Minimum-Variance & Maximum Sharpe Ratio Theoretical Portfolios



Source: Clare, Motson and Thomas (2013)

The second group of investors may have alternative preferences when allocating capital. Their investment decision is not solely based on the amount of risk they incur as the case of the minimum-variance portfolio investors. This group of investors are considered to have a higher risk tolerance compared to the previous group; however, they are still what we call rational investors since they consider both returns as well as the variance of returns when allocating capital to portfolios.

Sharpe (1966), in his paper *"Mutual Fund Performance"*, describes the key elements portfolio selectors consider as both expected return and risk. This is in clear contrast to the portfolio selector, who prefers the minimum variance portfolio. In selecting the optimal portfolio that provides the desired combination of risk and return, the investor needs to specify their preferences.

The final step for the investor would be to select a portfolio that plots on the efficient frontier that is deemed most desirable based on their expectations about risk and expected returns. Once this portfolio is selected, the investor needs to consider a few crucial aspects. Firstly, the forecasted portfolio performance is described by the expected rate of return (E_i) and the predicted risk or variability expressed as the standard deviation of return (σ_i).

Secondly, we assume that all investors can invest in a risk-free investment that generates one common interest rate and that these investors can similarly borrow funds at this rate. Third, we assume than at any point in time, all investors have the same future predictions about the performance of security prices. These conditions lead to the estimation of the capital market model, also known as the Capital Market Line (CML).

Portfolios that plot on the CML becomes the efficient frontier and can be expressed as:

$$E_i = p + b\sigma_i \tag{2.8}$$

Where

E_i	=	the portfolio expected rate of return
p	=	the pure riskless interest rate
b	=	will be assumed to be positive since investors are risk-averse

This relationship, initially described by Tobin (1958) and formally known as the separation theorem, is based on how investors firstly identify the optimal portfolio of risky assets and after that decide whether to lend or borrow, depending on their risk tolerance.

If investors can borrow or lend at a common riskless interest rate p and invest in a market portfolio with an expected return (E_i, σ_i), the investor can now allocate capital anywhere between the portfolio, the borrowing rate or the lending rate and obtain any point along the line:

$$E = p + \left(\frac{E_i - p}{\sigma_i}\right) \sigma \tag{2.9}$$

Any portfolio will generate a combination of the expected rate of return (E_i) and the predicted risk or variability expressed as the standard deviation of return (σ_i). The optimal portfolio will be the one for which $(E_i - p)/\sigma_i$ is the greatest. Sharpe (1966), initially defines this ratio as the reward-to-variability ratio, which has formally become known as the Sharpe Ratio (SR). The SR represents the expected return per unit of risk; thus the portfolio with the maximum SR as illustrated by point C in **Figure 2.3** provides the highest expected return E_i, per unit of risk σ_i. This is known as the optimal risk efficient portfolio or the "*tangency portfolio*", originally introduced over 50 years ago by Sharpe (1966), later revised by Sharpe (1994) and considered one of the most popular risk metrics in the investment management industry. The SR can also be interpreted as the CML since it is a measure of the total risk of the portfolio and most appropriate when analysing a portfolio of securities rather than one single security.

The Sharpe Ratio can be expressed as:

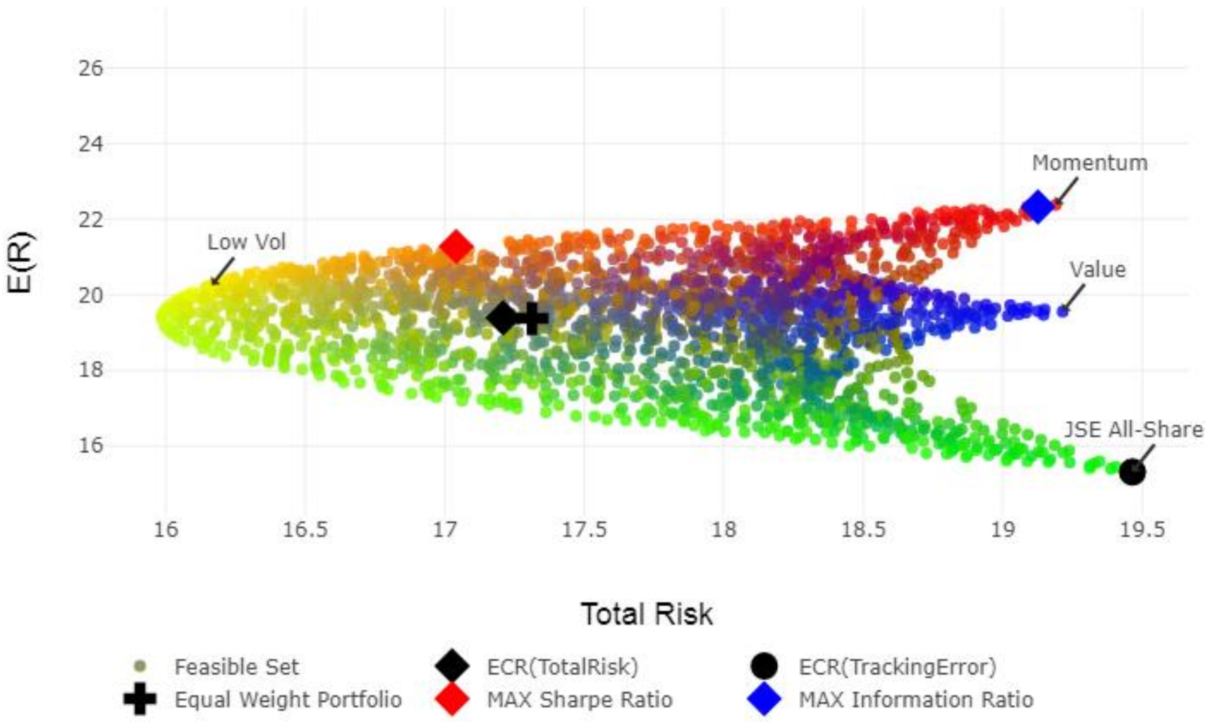
$$S_i = \frac{E(R_i - RFR)}{\sigma_i} \tag{2.10}$$

Where

R_i	=	the expected return of asset i
RFR	=	the risk-free rate of return
σ_i	=	the standard deviation of the returns for asset i

Higher SR's indicates superior risk-adjusted returns for a portfolio of securities. We construct a practical feasible set of portfolios to illustrate the optimal risk efficient portfolio, also known as the maximum Sharpe Ratio portfolio or the "*tangency portfolio*". The buildings blocks for this practical portfolio are identical to those used in the example previously illustrated in **Figure 2.2**. **Figure 2.4,** however, illustrates a representative sample of the feasible set which includes 2000 sample portfolios for the period 2006 – 2009 when the Global Financial Crisis (GFC) was in full effect and, security prices experienced high levels of volatility.

Figure 2.4: The Maximum Sharpe Ratio Portfolio for Practical Alternative Portfolios



Source: Authors depiction using A-Dex Prism

The results suggest that during the GFC, the maximum SR portfolio *(Sharpe Ratio of 0.72)* consisted out of a blend containing 48 percent Momentum Factor and 52 percent Low Volatility Factor. We see that holding the JSE All-Share Index alone over this period would have offered little return for its level of risk.

Evaluating the relationship between the efficient frontier, the minimum-variance portfolio, the maximum Sharpe Ratio portfolio and the CML, we conclude that the portfolio optimisation principle should take effect when investors know the relationship between risk and return and their preference to these two variables. Markowitz (1991) argues the optimal portfolio is the one tangent between the CML and the efficient frontier, therefore the maximum Sharpe Ratio portfolio.

2.3 Efficient Market Hypothesis and Random Walk Theory

The Efficient Market Hypothesis (EMH) which is widely known in portfolio management literature, as defined by Fama (1970) suggests that investors should not be able to outperform their peers on a risk-adjusted basis consistently. Reilly and Brown (2012) describe an efficient market as one in which security prices rapidly adjust to reflect the arrival of new information, and therefore one can assume that the current prices of securities reflect all available information about those securities. The question of whether security markets are efficient can be regarded as one of the most controversial within the area of investment management and investment research. The extensive research, particularly over the past 30 years regarding whether capital markets are efficient is vital since the results have material practical implications for investors and portfolio managers.

The EMH theory is based upon the notion that in an efficient market prices *"fully reflect"* available information. This theory is however, subjective and general. Fama (1970), therefore advises that a model needs to be designed to define precisely what is meant by the term *"fully reflect"*. One suggested model would be that equilibrium prices *"expected returns"* are generated as per the two-parameter world described by Sharpe (1964). When investors view the outcome of returns of an investment in probabilistic terms which describes the possible returns in terms of some probability distribution. In determining whether to proceed and allocate capital to a particular investment, the investors are willing to act on the basis of having only two-parameters in the probability distribution being: (1) the expected value and (2) its standard deviation. The two-parameters probability distribution can be represented by a total utility function expressed as:

$$U = f\,(E_W, \sigma_W) \tag{2.11}$$

Where

E_W	=	indicates expected future wealth
σ_W	=	indicates the predicted standard deviation of the possible divergence of actual future wealth from E_W

2.3.1 Weak Form EMH and Random Walk Theory

The weak form EMH originally stated that current stock prices fully reflect all market information, and therefore, we can assume that historical prices cannot predict future stock prices. Current stock prices reflect trading volume data and the historical sequence of that particular stock, thus following a *"random walk"*. One influential theory that has evolved in addressing and testing models of stock price behaviour is the theory of random walks. The random walk theory states that successive price changes are independent over time. The idea of random walks was initially based on the observations of English botanist Robert Brown when he noticed that grains of pollen suspended in water had a rapid oscillatory motion when viewed under a microscope (Brown, 1828). This phenomenon was also observed in gasses and later became known as Brownian Motion. The pioneering work of Robert Brown was largely ignored by the scientific community for some time, and it was only in 1900 that the idea of Brownian motion or random walk theory surfaced in economic literature. The model of stock price behaviour was initially hypothesised in 1900 by Louis Bachelier, in his ground-breaking contribution in the construction of a random walk model for both security markets and commodity markets.

On April 1925, a dinner meeting of the American Statistical Association was held in New York, with approximately 420 people attending the meeting. The topic to be discussed at the meeting was Forecasting Security Prices. The program was closed by Frederick R. Macaulay of the National Bureau of Economic Research, who observed that there was a striking similarity between fluctuations in the stock market and that of a chance curve as obtained by throwing a dice (The American Statistical Association, 1925). Further empirical findings on the randomness of stock market movements and the ability, or rather inability of investors to accurately forecast stock returns were astonishing. Cowles (1933) initially evaluated the results achieved by 24 financial publications that forecasted the expected returns of the stock market during the period of January 1928 to June 1932. The results showed little evidence of skill in predicting the outcome of market prices. Further evidence of the lack of investors forecasting ability was presented by Cowles (1944) when he evaluated 11 forecasters, with 7 covering $15\frac{1}{2}$ years from January 1928 to July 1943 and the remaining 4 forecasters covering 11 years ending in 1938 and 1939. The forecasters included 4 well known financial periodicals and 7 well known financial services.

The results once again proved to be astonishing as:

- 11 well-known periodicals and financial services since 1927, for periods between 10 to $15\frac{1}{2}$ years, failed to show evidence of their ability to accurately predict the future outcome of the stock market as imitated by the Standard & Poor's average of 90 representative stocks.

- Most remarkably, it was noted that the forecasting agency that produced the best results *"evidence of skill"* for the $15\frac{1}{2}$ years since 1927, generated a mere 3.3 percent per annum return greater than a strategy than simply held stocks composed of the Dow-Jones Industrial Average. Cowles (1944) commented, *"Under present laws the capital-gains tax might wipe out most of this advantage."*

It was concluded that the success of the forecasting agency over this particular period was not completely accidental. Statistical tests indicate a simple application of the *"inertia"* principle, trading at turning points such as buying low after prices for a month averaged higher, and selling high after they averaged lower for the previous month, would have resulted in material returns which were substantially more significant than those of the forecasting agency (Cowles, 1944).

Kassouf (1968) in his article titled *"Stock Price Random Walks: Some Supporting Evidence"* further explores whether stock markets follow random walks. If stock prices follow random walks in which future steps, directions or movements of stock prices cannot be predicted based on historical price sequences as per the book: A Random Walk Down Wall Street Malkiel (1973) then, the price changes per unit of time would have a normal distribution. If the random walk theory is an accurate description of reality, then the numerous "technical" or "chartist" methods of predicting stock prices are fruitless (Fama, 1995). Moreover, technical and fundamental theories are considered by both market professionals and academics to be the essence of investment management and security selection. Random walk theorists base their beliefs on the premise that stock exchanges are not efficient. As described by Fama (1995), an efficient market is one where a large number of rational investors actively compete against one another to maximise their profits. These investors intend to predict the future market prices of securities using current information that is available to all market participants.

If security prices are independent *"random"*, we can conclude that buying a security and holding it will generate profits that are greater or equal to that of buying a security based on historical price changes. The tests for independence have produced consistent and impressive results, and Fama (1995) goes as far as to state: *"I know of no study in which standard statistical tools have produced evidence of important dependence in series of successive price changes"*.

If all of the above holds, stock markets would be unpredictable and successive security price changes would be independent of each other, implying they follow a random walk.

2.3.2 Semi-Strong Form EMH and Fundamental Analysis

"A stock is not just a ticker symbol or an electronic blip; it is an ownership interest in an actual business, with an underlying value that does not depend on its share price."

- Benjamin Graham

According to the semi-strong form EMH, security prices adjust rapidly to the release of all public information and current security prices fully reflect all available public information. Numerous studies including Ball and Brown (1968) on the impact of earnings announcements and Fama, Fisher, Jensen and Roll (1969) on the impact of stock splits and dividends, confirm the notion of the semi-strong form EMH in that no material price changes arise following stock splits or earning announcements due to the fact that any relevant information, i.e. earnings growth, has already been discounted in the current share price.

This section of the paper is particularly interested in the theory of fundamental analysis and the implications of a semi-strong form EMH on this theory. If investors are determined to construct the optimal risky portfolio, it is vital that we understand the components of that portfolio, *i.e. active vs passive vs enhanced indexation, value vs growth vs quality and fundamental vs quantitative*. Benjamin Graham is hailed as the father of fundamental analysis, his first book titled *"Securities Analysis"* published in 1934 is considered the foundation of fundamental analysis. Fundamental analysis can be defined as the process of analysing all aspects related to the economic wellbeing of a company, from its market share to the quality of its management. Fundamental analysis can be applied to determine whether a company's revenue is growing, is the company able to repay its debt and is the company generating a profit. In short, we can define fundamental analysis as a stock valuation methodology that considers financial and economic data to forecast the future movements of stock prices. Of course, fundamental analysis as a method of determining the future movements of share prices encompass several, if not hundreds of methods and data points and can include company-specific data as well as macro-economic data.

"Valuation is easy. The tough part is fundamental analysis."

- Phil Friedman, former Morgan Stanley Portfolio Manager

The relevance of fundamental analysis, to the fundamental investor, is centred around the notion that in the long term, stock prices tend to revert towards its actual intrinsic value. The fundamental investor would use fundamental analysis techniques to determine a company's intrinsic value. If this intrinsic value is above the current market price, the investor will acquire the stock because they believe it would rise towards its intrinsic value, i.e. the stock is considered to be *"cheap"*. On the other hand, if the investor determines that the intrinsic value to be below the current market price, they would sell the stock because they believe the price would decline in value and move towards its intrinsic value, i.e. the stock is considered to be *"expensive"*.

Pearce and Roley (1985), in their influential paper *"Stock Prices and Economic News"*, evaluate the impact of announcements about macro-economic factors including money supply, inflation, real economic activity and the Federal Reserve's discount rate. Their results are impressive and suggest that the impact of macro-economic events on stock price movements failed to persist beyond the day of their announcements. Furthermore, the anticipated components of macro-economic announcements significantly fail to affect the movements of stock prices on a daily basis. These findings are consistent with the theory of a semi-strong form efficient market in that security prices adjust rapidly to the release of all public information. We conclude that investors who base their investment decision solely on macro-economic variables and unexpected announcements about them will struggle to outperform their peers consistently. There are however, observable drifts in stock prices subsequent the announcement of important news for several months (Kothari & Warner, 1997).

In a study conducted by Shiller (1981) on the reaction of stock prices to changes in dividend policy found that stock prices are too volatile in the short term to be explained by changes in dividends only. More recent studies on share price reactions following public news by Chan (2003) compare returns of shares with public news to similar returns without evidence of public news and find a difference between the two sets. Stocks with news exhibit momentum either in a positive or negative direction, while stocks without news fail to exhibit momentum. The results surrounding drifts in stock prices indicate that although security prices in a semi-strong efficient market adjust to reflect all information, there is room for active managers to employ fundamental analysis to exploit these drifts. Information flows can certainly cause anomalies that contradict the semi-strong EMH.

Benjamin Graham, in his second book titled *"The Intelligent Investor"* initially published in 1949, stresses the importance of buying securities when they trade below their intrinsic value. This term formally became known as value investing. Methods of identifying these securities as described by Graham and Dodd (1934) and Graham (1949) include companies trading at a discount to book value, i.e. low price-book value *(P/BV)* ratios and those having low price-to-earnings *(P/E)* ratios. Initial empirical studies conducted by Rosenburg, Reid and Lanstein (1985) introduces a B/P *(Book Value/Market Price Per Share)* strategy in which they buy stocks on the New York Stock Exchange with a high B/P ratio and sell stocks with a low B/P ratio. They find a positive relationship between the B/P ratio and future stock returns and conclude the relationship between publicly available information on the B/P ratio and future returns contradict the semi-strong form EMH.

Fama and French (1992) evaluate the cross-section of expected returns by including variables such as market beta, size, earnings-price *(E/P)* ratio, leverage and the book-market value *(BV/MV)* ratio and find evidence of a positive relationship between *BV/MV* and average returns. Results of Basu (1977), support the original ideas of Benjamin Graham that value investing can be implemented as a sound investment strategy and that low P/E stocks generate superior risk-adjusted returns compared to high P/E stocks. The "*size-effect*" is another anomaly that points to the misspecification of the CAPM as the results of Banz (1981) show smaller firms generated significantly higher risk-adjusted returns compared to larger firms over a period spanning forty years. One possible explanation of the *"size effect"* is the fact that securities with small market capitalisations *"small-caps"* often fail to do exhibit sufficient information for risk-averse investors to determine their true risk parameters and expected return distributions. Investors would, therefore, choose not to hold securities of very small firms due to the lack of information available, and it is the lack of holding these small firms that eventually lead to higher returns for the "undesirable stocks" of small firms (Banz, 1981).

2.3.3 Strong-Form EMH

The final sphere of market efficiency is the strong-form EMH which encapsulates both the weak-form and the semi-strong form EMH. The strong-form EMH states that security prices reflect all information, including public and private firm-specific information. Research in favour of the strong-form EMH include that of Jensen (1969) in that mutual funds, and their security analysts fail to generate efficient portfolios as they underperformed the market portfolio. The reason for their underperformance is mainly due to a lack of superior forecasting ability and that prices of securities behave according to the strong-form EMH. Therefore, these prices reflect all available information, public and private. If the strong-form EMH cannot be rejected, the implications are that investors who use charts *"technical analyst"*, investors who use company-specific information *"fundamentalists"* as well as corporate insiders, security analysts and professional money managers should not be able to generate above-average returns consistently. The majority of studies conducted before 2002 indicate that on a risk-adjusted basis, highly trained professional money managers failed to generate superior risk-adjusted returns compared to simply buying the benchmark index. Net of fees, approximately two-thirds of mutual funds failed to generate returns better than the market. Moreover, mutual funds and security analysts failed to show consistency in their ability to generate superior returns. Interestingly, the only group who seem to generate above average returns are the largest endowments in terms of AUM. This is due to their ability and willingness to diversify their portfolios by investing in a wide variety of assets including hedge funds, FOF's, real estate and global alternative asset classes.

2.3.4 Market Efficiency in Emerging Markets

In order to construct the optimal portfolio using South African mutual funds, ETF's and style factors, we need to evaluate the efficiency of emerging markets before we start implementing the most desired investment management strategy. Our research so far has been limited to evaluating the efficiency of developed stock markets for which we have established that markets are not perfectly efficient.

A study examining the market efficiency of BRIC countries conducted by Mobarek and Fiorante (2014) find that BRIC stock markets are evolving towards a state of weak-form efficient, particularly over the period 2000 – 2010. Using data for the period 1995 – 2010, they find that during the initial period of the study these markets rejected the weak-form efficient market as they experienced significant positive autocorrelation in returns, thus not following random walks. In the latter part of their study, they find evidence that these markets have matured and can be considered efficient up to some extent.

De Souza *et al*. (2018) evaluates market efficiency by including South Africa, the latest member included in BRICS to investigate the profitability of technical trading strategies in BRICS member countries. They find that on average, the returns obtained from a TA strategy was positive. The results suggest that BRICS markets rejected the weak-form EMH and did not follow random walks. The study points out that market age and market efficiency is directly related since markets evolve to become more efficient over time. Brazil, the second oldest market included in the sample, generated the lowest returns using TA, implying the Brazilian market is more efficient than the other members. TA strategies in Russia and India generated the highest returns because these markets are younger, implying they are less efficient. Based on their results, they concluded that the weak-form EMH could be rejected for BRICS members. These results suggest that TA, along with fundamental analysis, can be used in emerging markets to generate above-average returns, particularly in younger emerging markets. Passive strategies should not be used in isolation when investing in these markets.

Noakes and Rajaratnam (2016) asses the efficiency of the South African market using random number generators. Using daily data for the period 2005-2009, they sort the shares in the sample according to their size as measured by their market capitalisation values into three categories; small, mid and large-cap. They divide the sample into two periods of market volatility; stable (March 2005 - July 2007) and unstable corresponding to the GFC (August 2007 - December 2009). Their results are inconclusive as to whether the JSE can be considered efficient or not. Small-cap stocks fail to exhibit random behaviour, while large-cap stocks fail to reject randomness. Their findings are similar to Smith and Dyakova (2014) in that efficiency is related to size. However, their results point towards size on a stock-specific level and not only on an aggregate exchange level. Thus, small stock exchanges, small-cap indices and small-cap stocks in Africa and South Africa are less efficient than large stock exchanges, large-cap indices and large-cap stocks. Stable periods lead to efficiency of JSE listed stocks while periods of a financial crisis (GFC) presents evidence against market efficiency. Efficiency and non-efficiency for JSE listed stocks can found in groups with similar attributes and characteristics such as size and liquidity on a stock specific level.

2.3.5 Conclusion: Market Efficiency in Developed and Emerging Markets

Overall, studies on the efficiency of developed markets have provided support for and against the existence of perfectly efficient markets. We conclude that the evidence of random walks supports the idea of the weak-form EMH. There is a large body of evidence that suggest additional firm characteristic and factors including *BV/MV*, *P/E* and *Size* explain their returns over and above their beta, which contradicts the semi-strong EMH. Our final synopsis is that developed markets are not perfectly efficient, and investors should consider incorporating passive investment strategies when markets are most efficient and active strategies when markets are less efficient. This will give portfolios exposure to beta when the market is efficient and alpha when the market exhibit lower levels of efficiency.

We find that developed markets exhibit higher degrees of market efficiency compared to emerging markets. African stock markets, including South Africa, incur periods of non-efficiency followed by periods of efficiency, thus successive periods of predictability and non-predictability. Our findings and the concept of the evolution of return predictability are consistent with the Adaptive Market Hypothesis (AMH) as described by Lo (2004, 2005,2012) in that investors are continually adapting to a changing environment and therefore, their investment strategies, techniques and policies are also formulated and adapted with this changing market environment in mind.

When markets are less efficient, profitable opportunities may present itself, which can be exploited by active portfolio managers. In the South African market, we encourage investment strategies to be dynamic and in line with the concept of AMH. Blending active and passive investment management techniques for various asset classes and stocks with heterogenous classifications and characteristics would be advantageous for investors allocating capital in the South African market.

Dragota and Tilica (2014) recommend the use of passive investment management strategies when markets and asset classes are more efficient, while less efficient markets and asset classes render active management strategies beneficial. This will enable investors to take advantage of markets when they are both highly predictable *"inefficient"* and non-predictable *"efficient"*.

2.4 Active vs Passive Portfolio Management

"Most investors will find that the best way to own common stocks (shares) is through an index fund that charges minimal fees. Those following this path are sure to beat the net results, after fees and expenses, of the great majority of investment professionals."

- Warren Buffett, *Berkshire Hathaway Inc. Chairman's Letter, 1996, pg 15.*

2.4.1 Introduction to Active and Passive Portfolio Management

Active portfolio management is forecasting (Grinold & Kahn, 2000). The sources of investment opportunity are essential in the context of active portfolio management. According to the fundamental law of active management, there are two sources of investment opportunity. The first is the investors' ability to forecast the residual return of each asset and asset class. The second source is the number of times per year active managers can implement their skill. The ability to forecast the residual returns of asset classes or individual securities is measured by the information coefficient, which is the correlation between the forecast and the eventual returns that were achieved. The information coefficient can be regarded as a measure of the level of skill the active manager has. Active investors are always looking for opportunities to purchase mispriced securities that are trading at prices below their intrinsic value as determined by rigorous fundamental analysis. Sharpe (1991) points out than an active investor's portfolio will differ from that of the passive investor almost all of the time. Active managers trade more frequently than passive managers, hence the term *"active",* leading to higher fees. Active investing can be considered a zero-sum-game (Sharpe, 1991).

Passive investing, on the other hand, through a market capitalisation-weighted index ETF or low-cost index fund aims to track and replicate as closely as possible the returns of a benchmark or specific market segment by investing in the securities or sample of securities that compose the benchmark or market segment (Rowley, Walker & Zhu, 2019). Any strategy seeking to differentiate itself from the benchmark index or market segment should be considered active management. Passive investing seeks to minimise the expected deviations of returns from that of the benchmark index, on the downside as well as the upside. Over the long term, passive investment strategies have proven to be beneficial to investors as it eliminates the need to find active managers who consistently generate above-average returns, see section 2.4.5.

2.4.2 Active vs Passive Portfolio Management in Developed Markets

Malkiel (1995) in his research titled *"Returns from Investing in Equity Mutual Funds 1971 to 1991"* supports the theory that historical price and security information does not lead to superior returns and that security prices reflect all available fundamental information in a rapid manner. By the 1970s, the EMH had become the accepted standard in the field of academia (Malkiel, 1995). However, by the 1980s some anomalies appeared that contradicts the EMH. During this period, security prices were not independent, did not follow random walks and showed positive correlations over the short term and negative correlations over long periods. This behaviour contradicted earlier studies conducted by Kendall (1953) and Osborne (1959) who found that serial correlation coefficients of stock returns were close to zero. Furthermore, by using fundamental variables such as dividend yields, market capitalisation, (size), *P/E* ratios and *P/BV* ratios, investors could find and forecast predictability in future stock prices, see Basu (1977), Rosenburg, Reid and Lanstein (1985) and Fama and French (1992). These anomalies have led to the ongoing debate, do active managers outperform their benchmark and passive strategies?

One of the first studies that assessed the performance and specifically the predictive ability of 115 open-end mutual funds for the period 1945 – 1964 was conducted by Jensen (1968). His study introduced two subsets of *"performance measurement"* when portfolios of risky investments are evaluated. One, the ability of security analysts to successfully predict future stock prices. Second, the ability of the portfolio manager to minimise portfolio risk. Therefore, the success of portfolio managers and security analysts is measured by their predictive ability. We can define this as the ability to generate returns by selecting stocks that produce higher returns than those which we could expect for the amount of risk incurred in the portfolio. Previous studies by Sharpe (1966) on the performance of mutual funds were based on relative measure of performance, i.e. ranking portfolios against each other and not against some absolute standard or measure. The study conducted by Jensen (1968) introduced an absolute measure to evaluate the forecasting ability of portfolio managers and is derived from the application of the CAPM. The model is similar to the SR developed by Sharpe (1966). However, this model includes an additional factor called *"alpha"* which represents the additional return produced in excess of what the asset should produce in a state of market equilibrium. CAPM indicates the return a security or portfolio of securities should generate for its degree of systematic risk, i.e. β_j. Starting with the original CAPM equation developed independently by Sharpe (1964), Lintner (1965) and Mossin (1966), which calculates the expected return for any security or portfolio of assets as:

$$E(R_j) = RFR + \beta_j\ [E(R_M - RFR)] \tag{2.12}$$

Since the expected return $E(R_j)$ of portfolio j and the risk-free rate RFR vary over periods of time t, we can express the CAPM in terms of realised returns rather than expected return $E(R_j)$:

$$R_{jt} = RFR_t + \beta_j\ [R_{mt} - RFR_t] + e_{jt} \tag{2.13}$$

Where e_{jt} is a random error term as the equation expresses the rate of return on a security or portfolio for a period of time as a linear function of the RFR_t, plus a risk premium $\beta_j\ [R_{mt} - RFR_t]$ that depends on the level of systematic risk, i.e. β_j plus a random error term.

This leads to the Jensen Alpha measure expressed as:

$$R_{jt} - RFR_t = \alpha_j + \beta_j\ [R_{mt} - RFR_t] + e_{jt} \tag{2.14}$$

The Jensen measure suggests that superior managers who can consistently forecast stock returns should earn higher risk premiums compared to those implied by $\beta_j\ [R_{mt} - RFR_t]$. Superior performance is detected by including an intercept term with a nonzero constant that indicates positive or negative divergence from the model. In Equation 2.14, α_j indicates the managers ability to forecast stock returns. Managers with superior forecasting abilities will have significant positive *"alpha"* α, compared to inferior managers who will generate returns less than those based on CAPM and therefore significant negative *"alpha"* α. Finally, managers with no forecasting abilities but who are not able to outperform the risk premium will equal a simple passive buy-and-hold strategy. α in the context of the Jensen measure indicates how much of the managers return can be attributed to their ability to generate superior risk-adjusted returns by identifying undervalued stocks. Jensen (1968) reports that 115 mutual funds, on average failed to possess superior stock-picking abilities in order to outperform a passive buy-and-hold strategy. The average fund β was only 0.840; thus, the mutual funds held less risky portfolios versus the market portfolio. The mean net intercept value, α was -0.011. Most importantly, Jensen (1968) highlights that before accounting for fees, the mutual funds also fail to generate positive intercept values since the average gross α was -0.004. For this period, a simple passive buy-and-hold strategy would have been more beneficial for the average investor compared to using active mutual funds to achieve their investment objective given their risk tolerance. Later studies conducted by Henriksson (1984), evaluate the market-timing performance of 116 mutual funds using monthly return data for the period 1968 – 1980. The empirical results derived using parametric and nonparametric tests found that active mutual fund managers failed to implement a strategy that times the return on the market portfolio (Henriksson, 1984). Moreover, active mutual fund managers were unable to forecast larger changes in the value of the market portfolio compared to smaller changes. In an efficient market, information should be freely available, and therefore, security prices should reflect all available information (Fama, 1970).

In an attempt to determine the benefits of active portfolio management in light of the costs involved in obtaining information, Ippolito (1989) uses the Jensen measure as per equation 2.14 to estimate the α and β for 143 mutual funds for the period 1965-1984. This study is comparable to several *"first-generation"* mutual fund studies that were published in prior years. However, it produced results different to those of Sharpe (1966), Jensen (1968) and Henriksson (1984). Ippolito (1989) finds evidence that active mutual funds, after accounting for fees and expenses, except load charges, outperformed passive strategies on a risk-adjusted basis. However, the average alpha produced by active managers is found not be higher than the load charges of the active funds. Thus, the positive alpha of active managers is eroded by fund expenses, management fees and charges. These results are consistent with the idea of the EMH and costly information and the notion that active investing can be considered a zero-sum-game (Sharpe, 1991). Ippolito (1989) does, however, find that active managers that are more active than their counterparts, i.e. higher portfolio turnovers, management fees and load charges can generate returns that offset the higher charges. This is in line with the notion that that active managers are efficient with regard to conducting research and executing trades. Malkiel (1995) evaluates mutual fund performance over the period 1971 – 1991 and permits measures of survivorship bias which form a substantial portion of the dataset. The results suggest that mutual funds underperform their benchmarks before and after accounting for management fees in the context of the CAPM. There is however, evidence that suggests the persistence phenomenon exists during some periods (1970) and breaks down during other periods (1980).

Investors would be better off following a simple, low-cost passive strategy compared to finding a *"hot-hand"* active manager, therefore in light of fees, performance and taxes, the advantages of passive investing outweigh active (Malkiel, 1995). Bogle (2010) states that he is a stronger believer in passive investing than he was when he created the first index fund in 1975. The concept of buying the market portfolio or index started off slowly, but has not only steadily gained acceptance by investors but has become a standard that dominates the debates about investment strategy, asset allocation and long-term portfolio construction. Bogle (2010) expresses his beliefs **(Table 2.1 & 2.2)** in passive management by presenting the absolute returns of average US equity mutual funds vs the S&P500 index for two distinct periods.

Table 2.1: S&P500 Index vs Equity Mutual Funds (Ended December 31, 1997)

Annual Returns Periods Ended December 31, 1997[1]

Period (Years)	S&P500 Index	Average Equity Mutual Fund	Index Advantage
50	13.10%	11.80%	1.30%
40	12.30%	11.50%	0.80%
30	12.50%	10.80%	1.70%
25	14.30%	13.90%	0.40%
20	17.40%	15.60%	1.80%
15	17.20%	13.20%	4.00%
10	18.60%	15.20%	3.40%
5	23.10%	18.10%	5.00%

Source: Bogle (2010: 148)

Table 2.2: S&P500 Index vs Equity Mutual Funds (Ended December 31, 2008)

Annual Returns Periods Ended December 31, 2008[2]

Period (Years)	S&P500 Index	Average Equity Mutual Fund	Index Advantage
50	9.20%	8.00%	1.20%
40	9.00%	7.60%	1.40%
30	11.00%	9.30%	1.70%
25	9.80%	7.70%	2.10%
20	8.40%	6.60%	1.80%
15	6.50%	4.80%	1.70%
10	-1.40%	-0.90%	-0.50%
5	-2.20%	-3.30%	1.10%

Source: Bogle (2010: 148)

[1] The average equity fund's returns include a 0.6 percent reduction for survivor bias and sales charges
[2] The average equity fund's returns include a 0.6 percent reduction for survivor bias and sales charges

From **(Table 2.1 & 2.2)** we find that for the 50 years up to 31 December 1997, the S&P500 Index outperforms the average actively managed equity mutual fund by an average of 2.30% in absolute terms over the entire timespan. For the 50 years up to 31 December 2008, the S&P500 Index outperforms the average actively managed equity mutual fund by an average of 1.31% in absolute terms over the entire timespan. The success of passive investing comes down to the extremely low-cost, its diversification benefits and the fact that the market capitalisation-weighted index consists mostly of large, high-grade stocks (Bogle, 2010).

2.4.3 Monkeys vs the Market-Cap Index

The market capitalisation-weighted index does, however, have its downfalls which we would like to highlight. Arguments in favour of market capitalisation index are based on the notion that the market index is mean-variance efficient. Clare, Motson and Thomas (2013) evaluate alternative approaches compared to the traditional market capitalisation-weighted index for the period 1968 to 2011. They make use of the fundamental index approach consisting of factors that include total annual dividends, total annual cash flow, book value and total annual sales from 1000 US companies listed on the NYSE, Amex and NASDAQ. They find that on a risk-adjusted basis, the fundamental index approach outperforms an index constructed based on the market capitalisation method from the same sample of 1000 stocks. Their market capitalisation index is derived by using the market capitalisation of each stock divided by the sum of the market capitalisation of the entire sample. Moreover, they randomly pick 1000 stocks from the sample to create an equally weighted index of 1000 stocks. If the computer program picks a single stock twice, its weighting would be 0.2 percent, three times and its weighting would be 0.3 percent and so on. If the program failed to pick a stock for the particular year, its weighting in the index would be zero. They find that US$100 invested at the beginning of 1968 would have achieved a terminal value of just under US$5000 if invested in the market capitalisation index, compared to just under US$9000 if invested in a randomly selected index of stocks that might as well have been chosen by monkeys.

2.4.4 Active vs Passive Portfolio Management in Emerging Markets

When information is very inexpensive, and analysts and traders have precise information at their disposal, then price equilibrium exists, and the prevailing prices of securities will exhibit almost all of the analysts and trader's information (Grossman & Stiglitz, 1980). However, in less efficient markets, investors can expect to see greater differences in returns between investors who spend large amounts of capital to gain advantageous information and investors who do not. In less efficient markets such as emerging markets and the South African market, the incentive to acquire advantageous information can be more significant and lead to superior returns versus passive strategies. Over the last 25 years, there has been a massive increase in the number of investment opportunities available to investors who wish to invest in emerging markets.

General emerging market studies of active equity mutual funds conducted by Huij and Post (2011) highlight performance persistence of emerging market equity funds. Their results do, however note several differences compared to the results of active US equity mutual funds. First, the consensus is that the results of US active mutual funds do not directly resemble the results of emerging market active mutual funds. Emerging markets, as highlighted in the previous section of this research, seem to be less efficient than developed markets which offer active manager the opportunity to general abnormal returns. Using monthly data attained from the CRSP Mutual Fund Survivorship-bias free database, they arrive at 137 emerging market equity funds that span over the period January 1993 to December 2006. Returns are compared to the S&P/IFC investable emerging markets index, which is an unhedged, market capitalisation-weighted index. The index includes securities from 22 emerging market security exchanges, including South Africa. They use several empirical tests to determine persistence, including the portfolio rank approach using monthly returns as well as the Sharpe Ratio and the Jensen Alpha time series approach. They find evidence that support performance persistency in emerging market equity funds and that funds that generated high (low) returns for the previous quarter tend to generate higher (lower) returns in the next month. Additionally, they find that the top ninth of active emerging market mutual funds included in their sample generates an outperformance of more than 4% per annum relative to the S&P/IFC investable emerging markets index and is statistically significant with a t-statistic of 1.95. These results and t-statistic are materially higher than those reported from studies covering US mutual funds.

Kremnitzer (2012) finds empirical evidence that there is a strong relationship between risk-adjusted, after fee returns of active emerging market funds relative to passive funds. Using 184 emerging market funds for the period 2009 – 2011, which represents three years following the GFC of 2008. The study finds that active emerging market funds generate on average net returns that were 2.87 percent greater than passive strategies. Gottesman and Morey (2007) examine numerous diversified emerging market fund specific characteristics. These characteristics including expense ratios, fund size, turnover, historical performance, manager tenure and Morningstar mutual fund star ratings to determine whether investors can use these characteristics to forecast emerging market mutual fund performance. Their study finds that only a single characteristic can consistently be used, namely expense ratio to forecast future mutual fund performance. Emerging market funds with lower expense ratios predict positive future performance and vice versa. They also find limited evidence that the 215 active emerging market funds for the period 1997 – 2002 managed to generate higher returns than that of the Vanguard Emerging Market Index Fund. This contradicts the findings of Grossman & Stiglitz (1980), Huij and Post (2011) and Kremnitzer (2012).

Initial studies on South African unit trusts when the industry was still in its infancy was conducted by Du Plessis (1974) and indicated that fund returns were positively correlated with fund risk as measured by systematic risk *"beta"* when evaluating only two unit trust funds that were benchmarked against each other. The first empirical evidence of performance persistency in the South African was highlighted by Gilbertson and Vermaak (1982) when they studied 11 South African unit trusts for the period 1974 – 1981. Their results were that on average, the absolute performance of all 11 unit trusts failed to outperform three different benchmarks. However, on a risk-adjusted basis using the Treynor, Sharpe and Jenson measures, they found that the active unit trusts outperformed all three indices. Moreover, Gilbertson and Vermaak (1982) found that one unit trust showed empirical evidence of persistent outperformance versus the three benchmark indices as well as the other 10 unit trusts. The results of Bertolis and Hayes (2014) indicated that over their entire investigation period of January 1994 to December 2012, the risk-adjusted returns of South African unit trusts during stable periods of economic growth was not statistically significant from the performance of the aggregate market. Interestingly, in contrast with periods of stable economic growth, Bertolis and Hayes (2014) found that South African unit trusts displayed significant risk-adjusted outperformance during periods of strong economic growth.

2.4.5 The Famous Active vs Passive Bet and its Association to EMH Theory

This research wishes to present a famous case study that attempts to give the reader insight and potential real-life applications of the theory of active and passive portfolio management we have discussed so far.

In 2008, at the height of the GFC, legendary investor Warren Buffett, made a US$ 1 Million bet in favour of the EMH and passive management. Buffett, issued a challenge to Protégé Partners LLC that the Vanguard S&P 500 Admiral fund *(VFIAX),* a low-cost passively managed index fund that aims to replicate the performance of the largest 500 companies in the US would outperform the average return of five actively managed hedge funds chosen by Protégé Partners LLC over a period of ten years. This was a simple challenge, putting the theories of active vs passive management to the test. The outcome; Buffett won. By the end of 2016, Buffett's Vanguard S&P 500 Admiral fund *(VFIAX)* generated a CAGR of 7.1 percent per year and a total return of 85.4 percent compared to the average return of the five active hedge funds chosen by Protégé Partners LLC, that merely generated 2.2 percent per year and a total return of only 22 percent. Buffett attributed his success to the fact that over ten years, a simple buy and hold passive strategy would outperform actively managed hedge funds after accounting for management fees, performance fees and other expenses. Protégé Partners LLC made a very valid argument in stating that the aim of hedge funds is not solely to outperform the benchmark index, its aim, however, is to generate positive returns over a predetermined time horizon regardless of the returns that were generated by the benchmark index.

The intricacies of this famous bet is in line with what our study sets out to examine; how can one blend active and passive investment strategies to complement each other when markets are not perfectly efficient?

2.4.6 Conclusion: Active vs Passive Portfolio Management in Developed and Emerging Markets

Evidence on active versus passive portfolio management in developed and emerging markets are in agreement that emerging markets are less efficient than their developed counterparts. Emerging markets, including South Africa, present more significant opportunities for active fund managers to generate superior, benchmark beating returns using their skill and informational edge. This research recommends investors, and professional money managers to exploit the *"hot-hands effect"* by investing in active managers who consistently prudence superior risk-adjusted returns. Passive strategies remain attractive building blocks for investors who wish to invest in low-cost, highly diversified portfolios in emerging markets.

2.5 Bridging the Active Passive Gap with Smart-Beta

"The most evident benefits of smart beta investment styles include its liquidity, diversification, extensive investment capacity, cost comparison, representation of the broader market, low turnover and ease of implementation and monitoring"

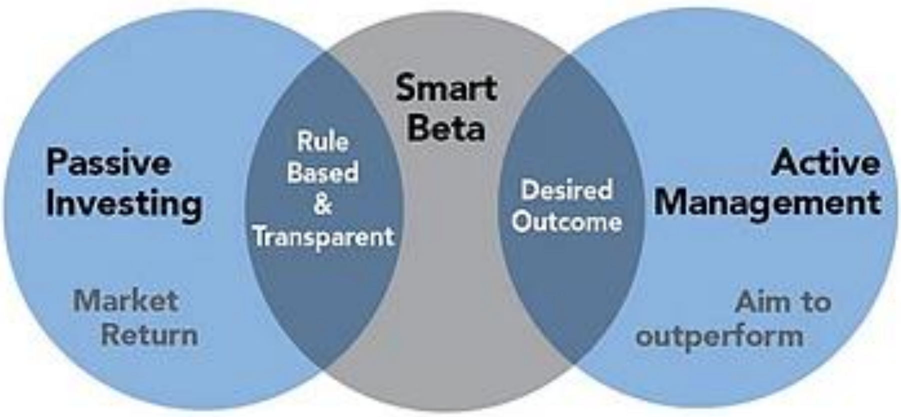
- Arnott, Hsu and West (2008)

Smart-beta, fundamental indexation or factor investing is one of the most recent additions to the range of investment styles, internationally and locally. Smart-beta, in short, refers to the idea of a semi-passive investment strategy than is constructed using specific fundamental factors. Factors or styles, formally grouped as clusters, can include volatility, value, size, momentum, liquidity, profitability, investment, and high yield. Smart-beta is a low-cost alternative to market capitalisation-weighted passive strategies while taking advantages of numerous active management traits that compliment the risk budgeting process. Adding factors to active and passive strategies improves information ratios while maintaining the portfolio characteristics and stock selection alpha of the original strategies (Melas, Nagy, Kumar & Zangari, 2019). The numerous advantages of smart-beta have made it a trendy alternative over passive and active management, and as investors have become more informed about these advantages, they have started adopting this alternative investment strategy. Smart-beta, also known as *"strategic beta", "advanced beta", "beta plus"* or *"beta prime"*, has experienced astonishing growth over recent years. Arnott, Hsu and Moore (2005) state that the excess return from the fundamental index portfolio compared to the market portfolio (S&P500) can be attributed to the following:

1. The superior construction of the market portfolio,
2. Price inefficiencies,
3. Additional exposure to distress risk, or,
4. A combination of all three,

Arnott, Hsu and Moore (2005) concluded that fundamental index portfolios are robust and significant due to their mean-variance superiority compared to the market capitalization-weighted index (S&P500 or JSE All Share). Moreover, if investors are seeking higher mean returns and lower total return volatility, and they believe fundamental indices will continue to generate robust returns in the future, then investing in fundamental indexation metric market indexes, or style clusters will generate higher Sharpe Ratios and will, therefore, be more beneficial to the end investor (Arnott, Hsu & Moore, 2005). Jacobs and Levy (2014) describe factor investing as a form of passive investing because it uses rules-based selection and weightings with rebalancing at fixed intervals. Besides, smart-beta does not attempt to forecast earnings, cash flows, profit margins and risks of individual securities. Some criticism of smart-beta strategies highlighted by Jacobs and Levy (2014) include the fact that smart-beta strategies are neither forward-looking nor dynamic. Factors and their weightings are determined at the outset of the strategy using historical data. **Figure 2.5** demonstrates the idea of smart-beta and why it bridges the gap between active and passive portfolio management.

Figure 2.5: Smart-Beta Combines the best of Active and Passive

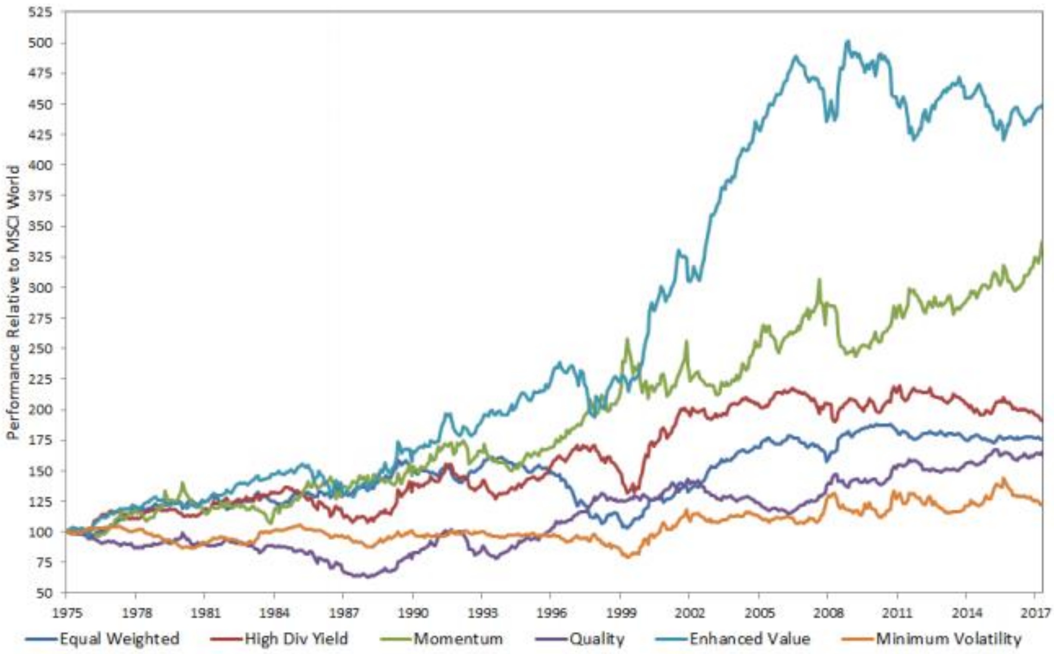


Source: BMO Global Asset Management

2.5.1 Smart-Beta Factors

Van Heerden (2014) identifies a variety of possible smart-beta factors to consider in the South African market. The factors include liquidity, momentum, age, price-to-book value, low risk, stock buybacks and management ownership. Van Rensburg (2001), in his seminal paper, *"A decomposition of style-based risk on the JSE"* documents several CAPM anomalies associated with smart-beta factors in the South African market. He creates three clusters from the smart-beta factors, namely value cluster, quality cluster and momentum cluster, which is represented by earnings to price, market capitalisation and twelve month past positive returns, respectively. Internationally, it has been suggested that the core fundamental factors or clusters that should be considered include value, momentum, quality, low volatility, size and yield (MSCI, 2018). Morgan Stanley Capital International FaCS developed an international factor classification standard that provides a framework for evaluating, implementing and reporting factor allocations across six persistent equity risk premia factors that include: value, momentum, quality, low volatility, size and yield. MSCI (2018) reports that the MSCI Factor Indexes have demonstrated long-term outperformance compared to their market-capitalization-weighted parent indexes. **Figure 2.6** illustrates the performance of MSCI Single Factor Indexes Relative to MSCI World Index as gross cumulative returns in US$ from 30 November 1975 to 28 February 2018.

Figure 2.6: MSCI Single Factor Indexes Relative to MSCI World Index



Source: MSCI (2018)

Investors can hold smart-beta funds or clusters as tactical allocations with their portfolios alongside active and passive market cap investments. Based on current economic conditions, market cycles or perception of a particular style factor, investors can rotate in and out of single factor index-based funds. **Table 2.3** indicate the benefit of investing in smart-beta factors over the long term.

Table 2.3: Summary Statistics for MSCI Single Factor Indexes (1975 – 2018)

	MSCI World	World Equal Weighted	World High Dividend Yield	World Momentum	World Quality	World Value	World Low Volatility
Total Return (%)	10.50	12.00	12.20	13.70	11.80	14.50	11.00
Total Risk (%)	14.40	15.20	13.90	15.50	14.00	15.90	11.50
Return/Risk	0.73	0.79	0.88	0.88	0.91	0.91	0.96
Max Drawdown (%)	53.70	55.80	58.80	52.50	44.50	57.90	43.00
Active Return (%)		1.50	1.70	3.20	1.30	4.00	0.50
Tracking Error (%)		4.90	5.90	8.00	5.60	6.30	5.90
Information Ratio		0.30	0.29	0.40	0.23	0.63	0.09

Source: MSCI (2018)

The historical disparity in the performance of individuals factors has motivated investors to consider combining different factors to achieve smoother performance over the long term. The low and even negative correlations between single factor indexes **(Table 2.4)** point out that investors who wish to invest in style factors should consider selectively combining factors, since it could reduce the overall volatility and risk of the consolidated portfolio. Additionally, blending specific style factors (i.e. momentum) with an active manager who have a style bias towards value, could increase the overall diversification of the portfolio. Correlations calculated by MSCI (2018) are for periods greater than 40 years and are therefore robust and statistically plausible going forward.

Table 2.4: Active Return Correlations for MSCI Factor Indexes (1975 – 2018)

	Size	Yield	Momentum	Quality	Value	Low Volatility
Size	1.00					
Yield	0.26	1.00				
Momentum	-0.11	-0.03	1.00			
Quality	-0.19	0.40	0.22	1.00		
Value	0.60	0.48	-0.06	0.10	1.00	
Low Volatility	0.12	0.44	0.11	0.19	-0.03	1.00

Source: MSCI (2018)

2.5.2 Value Factor in South Africa

Rousseau and van Rensburg (2003) find that the upside to value investing for South African investors become both larger and more reliable as their holding period increases. Value investors in South Africa are rewarded for their time in the market and not timing the market. They find that over more extended periods, value portfolios have more significant upside potential in terms of returns rather than downside potential in terms of losses. Rousseau and van Rensburg (2003) use dividend-adjusted returns for a sample of JSE stocks that focus on large capitalisation stocks over the period January 1982 to August 1998. The sample represents the largest 100 shares on the JSE. They use a simulation study methodology in which all shares in the sample are ranked according to their P/E ratios. Five time horizons are examined in their study where they hold the portfolio for 6, 12, 18, 24 or 30 months. This method provides the distributions of the returns of 30 permutations of portfolio formation rules and time horizons. They find little divergence in the returns between low P/E and high P/E stocks over a 6-month time horizon. However, for periods greater than 18 months, they find that portfolios with low P/E's outperform portfolios with high P/E's. Additionally, Rousseau and van Rensburg (2003) find that it is a small portion of the shares in the sample that constitute the most substantial part of the value effect. They conclude that the best value strategy would be to construct a portfolio based on shares that were cheap over the previous periods as current low P/E shares are likely to exhibit weak price momentum. These results can be used in the context of blending value and momentum strategies when constructing a consolidated portfolio of style factors. Van Heerden and van Rensburg (2015) find that value portfolios offer significant outperformance across all sample periods, irrespective of whether returns are adjusted for risk, making this a robust and reliable strategy over the long term.

2.5.3 Momentum Factor in South Africa

Momentum and price reversal effects on the JSE are less documented compared to factors such as value, size and growth. Van Rensburg (2001) finds evidence of a possible momentum effect on the JSE. Twelve month past positive returns represents the majority of the momentum style cluster in South Africa. Later studies conducted by van Heerden and van Rensburg (2015) Use cross-sectional regression analyses, factor-portfolio analyses and multifactor analyses for 50 firm-specific factors for three sample periods from 1994 to 2011. They find that momentum portfolios successfully outperform over the entire sample period, however on a risk-adjusted basis, momentum portfolio fail to outperform. Van Heerden (2014) finds evidence of momentum effects, similar to the findings of Van Rensburg (2001), that the momentum style is present in South Africa market and can be represented by twelve month past positive returns. The momentum effect, is however diminishing when there is a lack of market depth. Market depth refers to the ability of market participants to execute relatively large trades without causing price fluctuations.

2.5.4 Low-Volatility Factor in South Africa

Volatility is a measure of the variation in returns of stocks. High volatility stocks are considered to have more risks associated with them, since the price tomorrow could be utterly divergent to the price today, compared to stocks that exhibit lower levels of volatility. The low-volatility effect, as explained by Blitz and Van Vliet (2007) refer to investments, particularly shares with lower total risk, however without lower returns. They present empirical evidence that stocks with low volatility have the ability to generate superior risk-adjusted returns. Blitz, Pang and Vliet (2013) investigate the empirical relationship between risk and returns in emerging markets since emerging markets have been characterised by high levels of volatility, particularly during several crises such as Mexico in 1994, Asia in 1997 and Russia in 1998. Using monthly data for the period 1988 – 2010 of stocks from 30 different emerging markets, with South Africa forming part of the sample. Initially, the total number of stocks in their sample is low. They document clear existence of a volatility effect in emerging markets. However, the relationship contradicts the CAPM in that risk and return in emerging markets have a flat and even negative relationship. Thus, one can construct portfolios that exhibit low levels of volatility without sacrificing potential excess returns.

2.5.5 Conclusion: Smart-Beta Strategies

This research confirms that the success of smart-beta investing is attributed to its ability to bridge the gap between active and passive investing. Investors should no longer consider whether or not to include smart-beta strategies to their portfolios. Their primary consideration now becomes choosing the best smart-beta strategy and manager.

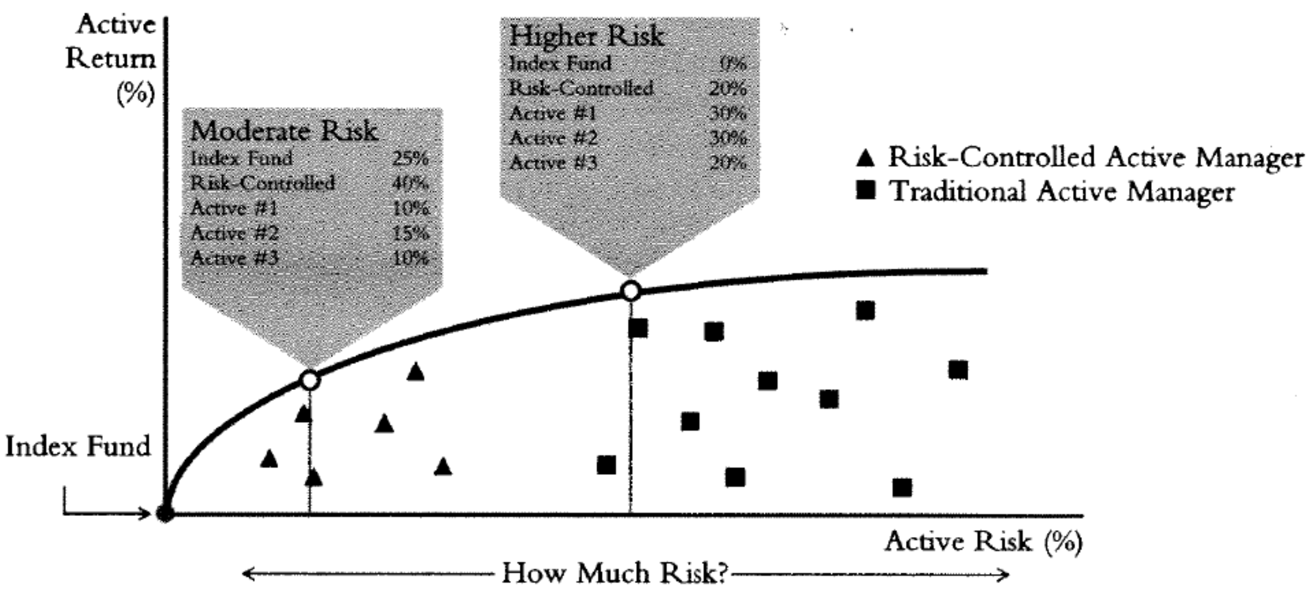
2.6 Risk Budgeting and Core-Satellite Portfolios

"Diversification is the only free lunch in investing."

- Harry Markowitz

Risk keeps investors up at night. The idea of risk budgeting as a portfolio optimisation technique has been explored by Waring *et al.* (2000) in which they present a methodology that solves structural problems involved when including active managers in the consolidated portfolio. They address how active risk, introduced to the portfolio through active managers, can be controlled as well as how active and passive managers should be held as a structure within the portfolio. Using S&P500 Growth and Value Index Funds, S&P500 Enhanced Index Fund with selection Alpha of 75 bps and three traditional active managers with expected selection Alphas ranging from 90 bps to 160 bps with the investor's benchmark being the S&P500. **Figure 2.7** illustrates the findings of Waring *et al.* (2000) in which they determine the optimal manager blend for the active risk budget of investors.

Figure 2.7: Different Active Risk Budgets Lead to Different "Core" Allocations



Source: Waring *et al.* (2000: 93)

Waring *et al.* (2000) suggest that investors with higher active risk budgets allocate ±80 percent of capital to active managers, investors with lower active risk budgets allocate ±100 percent of capital to Index and Enhanced Index Funds, while investors with moderate risk budgets allocate

±40 percent *(the most substantial portion of their capital)* to Enhanced Index Funds, ±25 percent to Index Funds and the remaining ±35 percent to active managers. Waring *et al*. (2000) answer the perplex question, active versus passive: the portfolio mix explicitly recommends a split between active and passive *(index strategies)* as a natural outcome of the optimisation conundrum. Their recommended mix justifies and encourages a substantial allocation to a *"core"* portfolio of low-cost, low active risk funds such as Index and Enhanced Index Funds. A recent study conducted by Vanguard (2017) indicate the benefits of core-satellite portfolio management are: (1) increases in overall portfolio diversification, (2) reduces overall fund management and transaction costs, (3) reduces key person risk as passive investment management strategies *"core"* don't rely on the skills of security analysts and portfolio managers as per the case of active managers, (4) increases in after-tax returns due to lower portfolio trading and turnover and (5) less reliance on active fund managers who aim to continually pick winning stocks.

2.7 The Rise of Robo-Advisors

Over the past decade, traditional financial advice as we know it has changed dramatically with the emergence of Robo-advisors (RA). RAs are possibly the most disruptive trend in wealth and asset management today (Beketov, Lehmann & Wittke, 2018). The term Robo-advisor has become a well-known buzzword with promising growth prospects in store for their services. Beketov *et al.* (2018) describe RAs as an *"automated investment platform that uses quantitative algorithms and techniques to manage portfolios and is accessible to clients online"*.

In a white paper published by Deloitte (2016), they highlight that Google search queries for *"Robo-advisors"* generate 423 000 results with close to 100 RAs in 15 countries around the world. It is estimated that by 2020, RA's will manage between US$2.2 trillion and US$3.7 trillion and by the year 2025, the AUM figure is forecasted to rise to over US$16 trillion, which is approximately three times greater than the AUM of BlackRock, the world's biggest asset manager to date. The primary reasons for the tremendous success of RA's come down to the following factors:

1. a new "next" generation client,

2. Several advantages of RAs over traditional financial advisors *(covered later in this section)*, and,

3. Large-scale financial processes such as the implementation of global wealth and the adoption of RAs in Asia

The wealth and asset management industry is evolving. The next generation client is highly receptive to digital technologies, vastly educated, prefers to have active and ongoing control over their investments and base their decisions on the information from numerous online sources rather than a single individual financial advisor. It is estimated that around 49 percent of high net worth individuals globally would consider RAs manage some portion of their total wealth (Beketov *et al*. 2018). The advantages of RAs over traditional financial advisors are highlighted by Rosenberg (2019) as:

1. Lower costs: RAs offer services at much lower costs compared to traditional human advisors. Schwab Intelligent Portfolios, charges nothing for its RA service. Investors only pay fees from the low-cost funds that are included in the portfolio. It is estimated that the average RA globally charges around 25bps – 0.35bps, which is four times greater than the average human financial advisor.

2. Global access from multiple devices: RAs provide investors with access to control, monitor and construct investment portfolios from multiple devices (smartphones, laptops, and tablets).

3. Methodical, quantitative and transparent approaches to constructing sophisticated portfolios: RAs use cutting-edge quantitative methods. Some RAs publish comprehensive methodological whitepapers that scientifically explain their investment strategies, see Wealthfront (2017).

4. RAs have low investment minimums: RAs allow investors to gain financial advice affordably while not having to invest a sizeable minimum lump sum. In addition to receiving calculated and prudent investment advice regarding factors such as asset allocations and investment horizons, investors gain access to low-cost passive and active strategies that meet their risk tolerance.

RAs can be classified into four broad classifications, as proposed by Deloitte (2016). These classifications are dubbed *"generations"*. The next generation of RAs and perhaps superior are the third and fourth generation of RAs. They use proven quantitative methodologies and algorithms to develop and manage portfolios. This study is particularly interested in understanding the third and fourth generation RAs who truly take over the work of traditional human financial advisors.

2.7.1 What are the Quantitative Methods Inside the Robots?

A recent study conducted by Beketov *et al*. (2018) investigates the processes followed by third and fourth generation of RAs and examines the asset allocation and portfolio optimization methods applied in existing RAs worldwide. They analyse 219 RAs that can be regarded as third and fourth generation in nature. Their sample comprised of RAs from 28 countries. Thirty percent of the RAs are located in the USA, 20 percent in Germany, 14 percent in the UK, 9 percent in Switzerland and the remaining 27 percent in other countries. All RAs included in the study were founded between 1997 – 2017. The average founding year is 2017. Founding years can be broken down into:

- 2017: 15 percent
- 2016: 48 percent
- 2015: 16 percent
- 2014: 14 percent

The RA with the lowest AUM was US$1 million, while the largest RA in terms of AUM was US$93 000 million. The average RA AUM was US$3 739 million, and the median RA AUM was US$93 000 million. Beketov *et al.* (2018) then analyse the occurrence of the methods inside RAs, i.e. the methodologies RAs use in constructing the optimal portfolios for their clients. For example, the terms *''Modern Portfolio Theory''* or *''Risk Parity''* refer to methodological frameworks used within the RAs. Other methods, including *''Black–Litterman model''* or *''Fama–French Factor model,''* refer specifically to these methods. The terms *"Sample Portfolio''* and *''Constant Portfolio Weights''* are classified as general terms since the RAs do not describe the actual underlying methodology for these terms.

Of the initial 219 RAs included in the sample, Beketov *et al*. (2018) only manage to identify 73 RAs that provide information regarding their quantitative methodologies in constructing portfolios and determining the optimal asset allocation for clients. In these 73 RA systems, they successfully find the names of 31 different methodologies used by RAs globally. It is no surprise that the most frequently applied methodology among RAs is Modern Portfolio Theory.

Table 2.5: Occurrence of different Methodological Frameworks within RAs Globally

Methodological Framework	Occurrence (%)
Modern Portfolio Theory	39.7
Sample Portfolios	27.4
Constant Portfolio Weights	13.7
Factor Investing	2.7
Liability-Driven Investing	2.7
Risk Parity	1.4
Full-Scale Optimisation	1.4
Constant Proportion Portfolio Insurance	1.4
Mean Reversion Trading	1.4
Other	8.2

Source: Beketov *et al.* (2018)

Among the three most common terms **(Table 2.5)**, only Modern Portfolio Theory can be called a quantitative methodological framework. The other two terms are general definitions which are unknown to the authors. Using all 2019 RAs in the sample, Beketov *et al*. (2018) illustrate the occurrences of mythological frameworks used by RAs in a word cloud **(Figure 2.8)** where the size of the names in the cloud are proportionate to the number of times they appear in the sample.

Figure 2.8: Word Cloud of the Occurrence of Methods used by RAs Globally

Source: Beketov *et al.* (2018)

Beketov *et al.* (2018) conclude that RAs who attempt to use more sophisticated methods when constructing portfolios attract higher AUM volumes although these methods are applied less often than the more straightforward and more generally defined methods. We can expect to see hybrid RAs in the near future that are intended to incorporate more human interaction during unusual or crises. Overall, we are confident of seeing several changes in the RA sector over the next five to ten years. The newer and more sophisticated methodologies will be extensively introduced in RAs, which are aimed at producing superior returns and can be used as a marketing tool to attract new next-generation investors.

2.7.2 Robo-Advisors in South Africa

Compared to the US and the UK, where RAs have been hugely successful in recent years, South Africa's RA market is still in its infancy. This is primarily because few FSP's have a large enough customer base and investment portfolio to achieve the required economies of scale that justify the implementation of automated RA's. However, it is forecasted that by 2023, Robo-advisors will manage approximately US$231 million in South African assets, up from only US$46 million in 2019. Compared to the United States, where Robo-advisors manage approximately US$749,703 million in 2019 (Statista, 2019). There is great potential for growth of RAs in South Africa over the next few years.

Only about 2 percent of South Africans have an annual income of more than R400 000 (SARS, 2017). Surprisingly, most people in the category have bought a financial product in the previous three years which indicate their appetite for financial products. Moreover, the greatest majority *(>90 percent)* acquired professional financial advice before they decided to proceed and purchase a financial product (Deloitte, 2018). This tells us South Africans require prudent financial advice and they are willing to pay for it. Moreover, a study conducted by Deloitte (2018) indicates South Africans are open to using automated financial advice, particularly individuals between the ages of 34-44 and the individuals most interested are those who earn less than R750 000 per annum. The South African pension market is the largest on the African continent, and therefore we have seen companies including Sanlam, Sygnia, ABSA, Anchor Capital and OUTvest develop their own RA services. These firms use interactive, web-based platforms that are attracting the next generation of investors and savers in South Africa.

Chapter 3: Methodology

"Every investment decision should be research-driven."

- Wim Rauwenhoff, *Robeco's first director (1933 to 1960)*

3.1 Risk Budgeting

At its core, risk budgeting is a portfolio optimisation technique of setting an acceptable target level of risk for the consolidated portfolio (Schneider & Sams, 2009). The idea of risk budgeting is to allocate risk efficiently across several risk mandates, investment management styles and asset classes in order to maximise returns while remaining within the specified risk parameters. The fundamental idea of risk budgeting is to decompose a measure of portfolio risk into contributions from the individual asset held in a portfolio of assets. Risk budgeting, as a portfolio optimisation technique, sets out to identify the assets that are most responsible for risk as well as allocating risk across assets.

The starting point is always a portfolio decomposition:

$$P = P_1 + P_2 + P_3 \tag{3.1}$$

Expressing a portfolio P as a sum of other portfolios P_i. The P_i's may be classified as holdings of individuals securities, assets, factors or idiosyncratic risks. The goal is to attribute the risk of portfolio P to the sub-components or holdings P_1, P_2 and P_3 in an additive way. For simplicity, we will start by decomposing the risk of a two-asset portfolio, asset 1 and asset 2 expressed as:

$$\begin{aligned} \sigma_p^2 &= w_1^2\,\sigma_1^2 + w_2^2\,\sigma_2^2 + 2w_1w_2\sigma_{12} \\ &= (w_1^2\,\sigma_1^2 + w_1w_2\sigma_{12}) + (w_2^2\,\sigma_2^2 + w_1w_2\sigma_{12}) \end{aligned} \tag{3.2}$$

From 3.2, we can decompose the variance of portfolio returns σ_p^2 into:

$$\begin{aligned} &(w_1^2\,\sigma_1^2 + w_1w_2\sigma_{12}) : \textit{variance contribution of asset 1} \\ &(w_2^2\,\sigma_2^2 + w_1w_2\sigma_{12}) : \textit{variance contribution of asset 2} \end{aligned} \tag{3.3}$$

An additive decomposition for σ_p can be defined by dividing each variance contribution by σ_p:

$$\sigma_p = \frac{\left(w_1^2\,\sigma_1^2 + w_1 w_2 \sigma_{12}\right)}{\sigma_p} + \frac{\left(w_2^2\,\sigma_2^2 + w_1 w_2 \sigma_{12}\right)}{\sigma_p} \tag{3.4}$$

3.1.1 Calculating the Risk of a Multi-Asset Portfolio

Expanding the set of assets in the consolidated portfolio, the risk *"variance"* of a multi-asset portfolio can be expressed as:

$$\sigma_p^2 = \sum_{i=1}^{N}\sum_{j=1}^{N} w_i w_j \sigma_{ij} \tag{3.5}$$

A three-asset portfolio's risk can be expressed as:

$$\sigma_p^2 = w_1^2\,\sigma_1^2 + w_2^2\,\sigma_2^2 + w_3^2\,\sigma_3^2 + 2w_1w_2\sigma_{12} + 2w_1w_3\sigma_{13} + 2w_2w_3\sigma_{23} \tag{3.6}$$

We notice that as more assets (N) are added to the portfolio, more covariance terms $(\mathrm{N}^2 - \mathrm{N})$ enter the equation for portfolio risk *"variance"* σ_p^2. The risk of any individual assets becomes less important, and we are now more concerned about the co-movement of assets with each other. For example, the computational inputs for a 200 share portfolio would have 200 variance terms (N), and 19 900 unique covariance terms $(\mathrm{N}^2 - \mathrm{N})/2$, thus a total of 20 100 inputs. This can be simplified by using an index approach where we ignore the covariance between individual assets and estimate how individual assets covaries with an index portfolio and therefore infer individual asset covariances. The market model can be estimated as:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \tag{3.7}$$

Where $Cov\left(\varepsilon_i, \varepsilon_j\right) = 0\ (i \neq j)$ is the important diagonality *(of residual covariance matrix)* assumption. We derive:

$$\begin{aligned} \sigma_i^2 &= \beta_i^2 \sigma_m^2 + \sigma_{\varepsilon i}^2 \\ \sigma_{ij} &= \beta_i \beta_j \sigma_m^2 \end{aligned} \tag{3.8}$$

Using the market model, the computational inputs for a 200 share portfolio would have 200 beta terms (N), 200 residual risk terms (N) and a single variance of the market term. Thus, a total of 401 inputs.

3.1.2 Euler's Theorem and Risk Decompositions

Leonhard Euler's theorem for homogenous functions can be used in order to decompose the risk of the portfolio into the risk contributed by each of its components. Since we are concerned about the portfolio variance σ_p^2 and the portfolio standard deviation σ_p as risk measures, we can derive functional risk decompositions. Portfolio risk measures that are homogenous functions of degree one in the portfolio weights, Euler's theorem provides a general method for additively decomposing risk into individuals asset contributions.

Euler's allocation theorem was justified by several authors, including:

- Litterman (1996) and Tasche (2000) state that Euler's theorem is fully compatible with economically sensible portfolio diagnostics and optimisation.
- Patrik *et al.* (1999) state that from a practitioner's viewpoint, the use of Euler's theorem regarding risk contributions naturally adds up to the portfolio-wide economic capital.

First, we define a homogenous function of degree one. Homogeneous function; a function f is homogenous of degree one if for any constant c:

$$c.f(w_1, \dots, w_N) \tag{3.9}$$

So, the key result in the case of volatility, where C refers to the covariance matrix:

$$\sigma_p\,(w) = (w'Cw)^{\frac{1}{2}}, \text{ is:}$$

$$\begin{aligned} \sigma_p\,(c.w) &= \left((c.\ w')C(c.\ w)\right)^{\frac{1}{2}} \\ &= c.(w'Cw)^{\frac{1}{2}} \\ &= c.\sigma_p\,(w) \end{aligned} \tag{3.10}$$

Thus, if every share's weight in the portfolio is increased by a factor c, then the portfolio's standard deviation (σ) also increases by c. Euler's theorem for homogenous functions: let $f(w_1, \dots, \; w_n) = f(w)$ be a continuous, differentiable and homogenous function of degree one in the variables w. Then,

$$\begin{aligned} f(w) &= \sum_{i=1}^{n} w_i \frac{\partial f(w)}{\partial w_i} \\ &= w' \frac{\partial f(w)}{\partial w} \end{aligned} \tag{3.11}$$

In our case, the Marginal Contribution to Risk (MCR_i) of asset i is expressed as:

$$\sigma_p\,(w) = \sum_{i=1}^{N} w_i\, MCR_i \tag{3.12}$$

Deriving the MCR_i:

$$\begin{aligned} \sigma_p\,(w) &= \sum_{i=1}^{N} w_i \frac{\partial f(w)}{\partial w_i} \\ &= \frac{\partial (w'Cw)^{\frac{1}{2}}}{\partial w} \\ &= \frac{1}{2}(w'Cw)^{-\frac{1}{2}}\,2Cw \\ &= \frac{Cw}{(w'Cw)^{\frac{1}{2}}} \\ &= \frac{Cw}{\sigma_p\,(w)} \end{aligned} \tag{3.13}$$

$$\Rightarrow \frac{\partial \sigma_p\,(w)}{\partial w_i} = MCR_i = ith\ row\ of\ \frac{Cw}{\sigma_p\,(w)}$$

In scalar form, $MCR_i = \frac{\sum_{j=1}^{N} w_j \sigma_{ij}}{\sigma_p}$

Using Euler's theorem, we can decompose the risk of a two-asset portfolio. Starting From equation 3.10:

$$\sigma_p\,(w) = (w'Cw)^{\frac{1}{2}}$$

The first step is to derive the marginal contributions to risk:

$$Cw = \begin{pmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{12} & \sigma_2^2 \end{pmatrix} \begin{pmatrix} w_1 \\ w_2 \end{pmatrix} = \begin{pmatrix} w_1\,\sigma_1^2 + w_2\sigma_{12} \\ w_2\,\sigma_2^2 + w_1\sigma_{12} \end{pmatrix}$$

$$\frac{Cw}{\sigma_p\,(w)} = \begin{pmatrix} (w_1\,\sigma_1^2 + w_2\sigma_{12})\,/\sigma_p\,(w) \\ (w_2\,\sigma_2^2 + w_1\sigma_{12})\,/\sigma_p\,(w) \end{pmatrix} \tag{3.14}$$

Thus from 3.14, we find the MCR:

$$MCR_1 = (w_1\,\sigma_1^2 + w_2\sigma_{12})\,/\sigma_p\,(w)$$

$$MCR_2 = (w_2\,\sigma_2^2 + w_1\sigma_{12})\,/\sigma_p\,(w)$$

The next step is to derive the contributions to risk (CRs) from the (MCR_i) of asset i. Recall from equation 3.12:

$$\sigma_p\,(w) = \sum_{i=1}^{N} w_i\,MCR_i$$

So,

$$\begin{aligned} CR_1 &= w_1\big(w_1\,\sigma_1^2 + w_2\sigma_{12}\big)\,/\sigma_p\,(w) \\ &= (w_1^2\,\sigma_1^2 + w_1 w_2\sigma_{12})/\sigma_p\,(w) \end{aligned}$$

$$\begin{aligned} CR_2 &= w_2\big(w_2\,\sigma_2^2 + w_1\sigma_{12}\big)\,/\sigma_p\,(w) \\ &= (w_2^2\,\sigma_2^2 + w_1 w_2\sigma_{12})/\sigma_p\,(w) \end{aligned}$$

Which takes us back to equation 3.4 where we derive an additive decomposition for σ_p :

$$\sigma_p = \frac{\left(w_1^2\,\sigma_1^2 + w_1 w_2 \sigma_{12}\right)}{\sigma_p} + \frac{\left(w_2^2\,\sigma_2^2 + w_1 w_2 \sigma_{12}\right)}{\sigma_p}$$

3.2 Tracking Error

Active portfolio managers seek to generate returns greater than their benchmarks while adhering to the mandates and constraints imposed by their clients. The most common constraint is the tracking error *(TE)*, also known as the *TE* volatility, however, in practice, the terms *TE* and active risk are most commonly used Tracking error indicates the amount of variability that exists among the individual data points that make up the portfolios average positive or negative excess return (Vanguard, 2009). When evaluating the consistency of active and passive managers, *TE* becomes an important statistic. *TE* can be defined using a range of statistical measures, including the correlation coefficient, which is regarded as a simple tracking measure. *TE*, active risk or *TE* volatility is often used in the context of mutual funds, hedge funds, ETF's and index funds and is calculated as the annual standard deviations of return differentials between a portfolio of assets and a defined benchmark *(ex-post or ex-ante)* (Ammann & Zimmermann, 2001). The most common tracking error measure *(TE1)* is frequently used in practice and uses the square root of the noncentral second moment of return deviations:

$$TE1 = \sqrt{\frac{\sum_k^n (R_{Pk} - R_{Bk})^2}{n-1}} \tag{3.15}$$

Where

R_{Pk}	=	return of the tracking portfolio in period k
R_{Bk}	=	return of the predetermined benchmark portfolio in period k
n	=	sample size

The tracking portfolio, *P* can consist of either active allocations in which the tactical asset allocation (TAA) weights change regularly or a passive portfolio in which the TAA and asset weights do not change as frequently. Ammann and Zimmermann (2001) further notes that equation 3.15 is similar to the standard deviation, however, because it is a noncentral measure, the measure is also affected by outperformance or underperformance relative to the benchmark. Let us assume an active portfolio manager has a *TE* of 3.5 percent, compared to an index fund that has a *TE* of 0.5 percent we can derive a practical and meaningful interpretation of this in that the index fund is tracking its benchmark more accurately compared to the active manager.

Ammann and Zimmermann (2001) demonstrate the concept using the following simplified example: if a portfolio exhibits 20 percent volatility and has a correlation coefficient of 0.95 with its benchmark, then the tracking error of the portfolio is 6.24 percent. Tracking error in this sense can easily be interpreted and applied to calculations of portfolio risk. Active investors are rewarded for generating returns higher than that of their benchmarks, passive investors, on the other hand, are rewarded for replicating the returns of their benchmarks as closely as possible. However, the one common goal shared between these types of investors is to minimise specific *TE's*. This objective, according to Roll (1992), is called the tracking error volatility (TEV) criterion and that investors who attempt to satisfy it fails to produce mean/variance efficient Markowitz portfolios. Active portfolios with low *TE's* will be dominated by portfolios with higher average returns, lower volatilities, but not necessarily lower *TE's*. Thus, Markowitz efficient frontier portfolios dominate *TE* efficient portfolios (Roll, 1992).

3.2.1 TE Constraints, TE Optimisation and TE Causes

The idea of portfolio optimisation by generating excess returns compared to a benchmark while constrained to *TE* is certainly non-trivial. In our analysis of *TE* and its contribution to portfolio optimisation, active portfolio managers who outperform their benchmarks incur a *positive expected TE* which is simply the absolute difference between the return of either an actively or passively managed portfolio and that of its benchmark. The risk related to *positive expected TE* is measured by the volatility of the difference between the active portfolio's returns and the returns of the benchmark, which we express as *TE*. Investors, using active and passive managers should, therefore, have the end goal of generating the highest expected relative return while minimising *TE*. *TE*, its optimal level and the portfolio's *TE* constraints are dependent on the risk profile of the investor and whether their investment policy targets outperformance vs benchmark, risk-return objective, low volatility or simply zero deviation from the benchmark. *TE* is frequently used by advisors, quantitative managers and ETF sponsors to determine and manage a portfolio's risk factors and their optimal exposures in line with the client's risk and return objectives. The most apparent causes of *TE* are due to; (1) the active manager who attempts to outperform the benchmark by holding an overweight position in securities vs the benchmark and (2) passive mandates replicating the benchmark using only a sample of the securities represented in the benchmark. Thomas, Rottschafer and Zvingelis (2013) highlight that the factors leading to excessive *TE's* for active managers are attributable to:

1. **Management fees, transaction costs, performance-based fees:** Active managers generally have higher fees due to the security analysts and portfolio managers they employ as well as higher transaction costs due to the annual portfolio turnover they incur. These factors support the idea that active investing can be considered a zero-sum-game (Sharpe, 1991).

2. **Security selection:** Active managers that are benchmark cognisant may sometimes hold securities in different weights compared to their benchmark or even securities that are not represented in the benchmark.

3. **Factor tilts:** Active managers may exhibit biases towards individual styles, factors or TAA tilts including value, momentum or low-volatility as well as sector over/underweights.

4. **Cash flow management:** Active managers will hold cash positions to accommodate daily or monthly inflows and outflows as well as cash positions that can be deployed in stocks when they present buying opportunities. This is based on the perception of mispricing and that these perceptions frequently change as market conditions change (Sharpe, 1991).

Looking at the causes of *TE* for passive portfolios such as ETF's and index funds, it is essential to mention that these strategies set out to replicate the benchmark as closely as possible. Therefore, passive strategies must minimise *TE*. However, Thomas, Rottschafer and Zvingelis (2013) identify and discuss several factors that cause passive strategies to exhibit *TE*:

1. **Expense ratios:** Although passive strategies have lower fees compared to their active counterparts, they still charge fees for replicating the benchmark index. Since there are no fees coupled to the benchmark index, we can expect to see some *TE* present in

passive strategies. ETF's and index funds seek to keep expense ratios as low as possible in an attempt to minimise the *TE* of the passive strategy.

2. **Execution of transactions and rebalances:** The higher the degree of transaction execution within the ETF or index fund to replicate the benchmark index, the lower the *TE*.

3. **Optimisation:** ETF's and index funds aim to generate the same performance profile as the benchmark index. This can either be achieved through full replication in which the passive strategy owns all the securities that constitute the index, and this is usually the case for larger and more liquid indices found in developed markets. Alternatively, they can use optimisation techniques in which they buy a sample of securities that best represent the benchmark index based on exposures, risks and correlations. Optimisation strategies are more likely to lead to higher *TE's* compared to full replication strategies.

TE is a valuable tool in evaluating manager performance compared to a benchmark. We will however, not use *TE* in isolation as it is best used in combination with other performance metrics such as the Sharpe Ratio *(SR)* and Information Ratio *(IR).* Portfolio optimisation in its purest form is a very general term and can be obtained by:

1. The most significant excess returns vs the benchmark without taking into account portfolio volatility (Roll 1992).

2. Incur the same level of volatility as the benchmark, while generating returns above the benchmark (Jorion, 2003)

3. The highest risk-adjusted return while satisfying the *TE* constraint on the *TE frontier* (Maxwell, Daly, Thomson, & van Vuuren, 2018).

This idea is synonymous with the findings of Amenc, Malaise and Martellini (2004) and the greater portfolio construction problem. When investors restrict their allocations towards active strategies due to tight tracking error constraints, they tend to forego opportunities of return enhancement and risk reduction. This is usually the case during periods of general market downturns as active and absolute return strategies tend to outperform passive investment strategies (Amenc, Malaise & Martellini, 2004).

3.3 Information Ratio

Utilising the literature from the Markowitz mean-variance paradigm we discussed in chapter 2.2, we will now incorporate the information ratio (IR) to our research. The IR is a measure that summarises the mean-variance properties of an active portfolio (Goodwin, 1998). The IR is often reported on glossy marketing brochures and factsheets of active managers any many investors rely heavily on the IR when allocating their capital. The IR is a very powerful tool when evaluating active managers and arguably the best standalone measure of the mean-variance properties of an actively managed portfolio. Simply put, the IR measures an active portfolio's average return in excess of a benchmark portfolio divided by the standard deviation of excess returns. Let R_{Pt} denote the return of an actively managed portfolio in period t and R_{Bt} the benchmark or index return, then we can derive the excess return ER_t as:

$$ER_t = R_{Pt} - R_{Bt} \tag{3.16}$$

We define $\overline{ER}$ as the arithmetic average of excess returns over the measurement period from $t = 1$ through T:

$$\overline{ER} = \frac{1}{T}\sum_{t=1}^{T} ER_t \tag{3.17}$$

We also include the standard deviation of ER from the benchmark, denoted as $\hat{\sigma}_{ER}$, also known as the *TE*-derived from equation 3.16. The IR can now be derived:

$$IR = \frac{\overline{ER}}{\hat{\sigma}_{ER}} \tag{3.18}$$

3.3.1 What does the Information Ratio have to do with Information?

The IR expresses the average ER per unit of volatility in ER. The ratio is often referred to as the *"alpha-omega ratio"* that stems from the Greek letters α and ω representing ER and idiosyncratic risk, respectively. However, we want to know what the ratio has to do with information. We attempt to answer this question using the theory set out by (Goodwin, 1998).

Starting with a variation of the linear market equation similar to the Jensen Alpha measure derived in chapter 2.4:

$$R_{Pt} - RFR_t = \alpha + \beta\, [R_{Bt} \; - RFR_t] + \varepsilon_t \qquad (3.19)$$

and,

$$\mathrm{var}(\varepsilon_t) = \omega^2$$

We can limit an active managers stock picks to a universe of securities or benchmark, and therefore, we assume the active manager incurs an equal amount of systematic risk as the market portfolio or index, i.e., $\beta = 1$. We can denote equation 3.19 as:

$$(R_{Pt} - RFR_t) = \alpha + [R_{Bt} \; - RFR_t] + \varepsilon_t \qquad (3.20)$$

Rearranged as:

$$\begin{aligned}(R_{Pt} - RFR_t) - (R_{Bt} \; - RFR_t) \; &= (R_{Pt} - R_{Bt} \;) \\ &= ER_t \qquad (3.21) \\ &= \alpha + \varepsilon_t\end{aligned}$$

Active managers can either generate returns that are superior or inferior to the benchmark index by underweighting or overweighting individual securities relative to the benchmark index. From equation 3.21, we see that the ER generated over the benchmark can be expressed as the sum of α plus residual risk (ε_t), and the IR becomes the risk-adjusted alpha:

$$\begin{aligned}IR &= \frac{\overline{ER}}{\hat{\sigma}_{ER}} \\ &= \frac{\alpha}{\omega}\end{aligned} \qquad (3.22)$$

The risk-adjusted alpha is generated from the under- and overweight security bets based on the information about the security or level of skill the manager has, thus the name IR. Grinold and Kahn (2000) develop a *"fundamental law of active management"* in which they construct a theoretical maximum IR (IR_{max}) that can be achieved by active managers. The IR_{max} consists of two components, namely the information coefficient IC and the breath of the strategy, denoted as BR. The IR_{max} can be expressed as:

$$IR_{max} = IC\left(\sqrt{BR}\right) \tag{3.23}$$

IC is the correlation between the actual returns of securities and the active managers forecasted returns. The IC is a measure of a manager's skill or special information and BR the number of independent bets taken on forecasts of exceptional returns (Grinold & Kahn, 2000). IR_{max} from equation 3.23 is an *ex-ante* ratio which does not represent the *ex-post* IR from equation 3.18. Deriving a strategy's IR_{max} becomes complex since most investors do not have access to active managers $IC's$ because they require in-depth security level forecasts that are proprietary. However, Grinold and Kahn (2000) support the notion of using historical information to calculate the *ex-post* IR from equation 3.18. Our analysis will, therefore, use the *ex-post* IR to assess the value of active managers within the core-satellite portfolio.

3.3.2 What is a Good Information Ratio and Warnings about the Ratio

If active managers achieve IR's of 0.50, it is *"good"*. An IR of 0.75 is *"very good"*, and an IR of 1.0 is *"exceptional"* (Grinold & Kahn, 2000). Additional remarks on the interpretation of IR's are made by Jacobs and Levy (1996) in that good active managers could generate IR's of 0.5 while exceptional managers could generate IR's of 1.0.

Goodwin (1998) mentions that investors should be aware of the following warnings when using the IR to assess the skill of active managers:

1. One, investors should avoid using the IR when making asset allocation decisions. This is because the IR is not a tool that is useful in evaluating asset classes and making decisions on how much capital to allocate to a particular asset class. Active equity managers and their IR's should not be compared to the IR's fixed income managers.

2. The IR does not make any implicit recommendation about the correlation and co-movements between securities and asset classes.

3. Moreover, the IR fails to take into account the risk tolerance and return objective of investors.

4. Finally, the active-passive trade-off should not solely be answered by assessing the IR of active managers. This is because active managers may outperform passive benchmarks during style-specific cycles. Thus, value managers may outperform passive and growth mandates while small-cap manager may outperform large-cap managers and vice versa.

3.4 Core-Satellite Portfolios

The central objective of this section is to derive the optimal blend between active, passive and smart-beta managers. Core-satellite portfolios consist of a passive core and active satellites (multiple specialist active managers or smart-beta managers). Using the information from chapter 3.1 – 3.3, we can determine the optimal allocation between multiple managers.

3.4.1 Optimal Manager Allocation Mechanics

Constructing a core-satellite portfolio using two managers, one active and one passive while adhering to a *TE* constraint is derived from Scherer (2002: 197-220):

$$\sigma_\alpha = \left(w_{\alpha_1}^2 \sigma_{\alpha_1}^2 + w_{\alpha_2}^2 \sigma_{\alpha_2}^2 + 2 w_{\alpha_1} w_{\alpha_2} \, \sigma_{\alpha_1 \;\, \alpha_2}\right)^{\frac{1}{2}} \tag{3.24}$$

Where σ_{α_i} (for $i = 1{,}2$) denotes the *TE* of manager i and w_{α_i} is the respective weight. The marginal contribution to active risk, or *TE* is expected to change if we increase or decrease the allocation to the active manager and can be calculates as the first derivative of the TE expression:

$$\frac{\mathrm{d}\,\sigma_\alpha}{\mathrm{d}\,w_{\alpha_1}} = \frac{(w_{\alpha_1})(\sigma_{\alpha_1}^2) + (w_{\alpha_2})(\sigma_{\alpha_1 \quad \alpha_2})}{\sigma_\alpha} \tag{3.25}$$

Multiplying this expression by ${}^{w_{\alpha_1}}\!/_{\sigma_\alpha}$ will produce the percentage active risk allocation for each manager:

$$\frac{\mathrm{d}\,\sigma_\alpha}{\mathrm{d}\,w_{\alpha_1}} \frac{w_{\alpha_1}}{\sigma_\alpha} = \frac{(w_{\alpha_1}^2)(\sigma_{\alpha_1}^2) + (w_{\alpha_1})(w_{\alpha_2})\,(\,\sigma_{\alpha_1 \;\, \alpha_2})}{\sigma_\alpha^2} \tag{3.26}$$

Finally, the two-manager allocation would be:

$$\begin{aligned}
&\frac{\mathrm{d}\,\sigma_\alpha}{\mathrm{d}\,w_{\alpha_1}}\frac{w_{\alpha_1}}{\sigma_\alpha}+\frac{\mathrm{d}\,\sigma_\alpha}{\mathrm{d}\,w_{\alpha_2}}\frac{w_{\alpha_2}}{\sigma_\alpha}\\
&=\frac{(w_{\alpha_1}^2)(\sigma_{\alpha_1}^2)+(w_{\alpha_1})(w_{\alpha_2})\ \sigma_{\alpha_1\ \alpha_2}}{\sigma_\alpha^2}+\frac{(w_{\alpha_2}^2)(\sigma_{\alpha_1}^2)+(w_{\alpha_1})(w_{\alpha_2})\ \sigma_{\alpha_1\ \alpha_2}}{\sigma_\alpha^2}\\
&=\frac{\sigma_\alpha^2}{\sigma_\alpha^2}\\
&=1
\end{aligned} \tag{3.27}$$

Using *"grid searching"*, we can determine the optimal blend between multiple managers by constructing several feasible sets or portfolios to find the optimal combinations of building blocks. The feasible set that produces the maximum IR or Sharpe Ratio while meeting the risk and TE constraints can be regarded as the optimal blend. The optimal bled is characterised by an equal ratio of marginal return vs marginal risk across all holdings, this ratio equals the optimal IR Scherer (2002: 199), expressed as:

$$\begin{aligned}
&\frac{\alpha_1}{\left(w_{\alpha_1}\sigma_{\alpha_1}^2+w_{\alpha_2}\,\sigma_{\alpha_1\ \alpha_2}\right)\big/\sigma_\alpha}=\frac{\alpha_2}{\left(w_{\alpha_2}\sigma_{\alpha_2}^2+w_{\alpha_2}\,\sigma_{\alpha_1\ \alpha_2}\right)\big/\sigma_\alpha}\\
&=IR_{total}
\end{aligned} \tag{3.28}$$

Equation 3.28 is the core guideline to optimal multi manager allocation within the greater portfolio. The equal contribution to risk portfolio can be derived by rewriting the above relationship between risk and return by expanding asset 1 and asset 2 with ${}^{w_{\alpha_1}}\!/_{w_{\alpha_1}}$ and multiplying the assets by σ_α:

$$\begin{aligned}
&\frac{w_{\alpha_1}}{\left(w_{\alpha_1}\sigma_{\alpha_1}^2+w_{\alpha_2}\,\sigma_{\alpha_1\ \alpha_2}\right)\big/\sigma_\alpha^2}=\frac{w_{\alpha_2}}{\left(w_{\alpha_2}\sigma_{\alpha_2}^2+w_{\alpha_2}\,\sigma_{\alpha_1\ \alpha_2}\right)\big/\sigma_\alpha^2}\\
&\frac{Return\ contribution_1}{Risk\ contribution_1}=\frac{Return\ contribution_2}{Risk\ contribution_2}
\end{aligned} \tag{3.29}$$

The foundation of core-satellite portfolios, using *TE* and variance constraints is that we should expect to see the IR and alpha of the portfolio to rise when *TE* rises due to investors conviction about the manager to outperform the benchmark. *TE* will also increase since a larger allocation to a single active manager will reduce the covariance i.e. diversification of the portfolio.

3.4.2 Why Multiple Strategies and Managers?

Adding a secondary manager or strategy to a portfolio increases the IR of the overall portfolio Scherer (2002: 201). What would happen to the portfolio IR if we include additional uncorrelated managers and strategies? And how many would we add? We can decompose these variables mathematically in terms of the portfolio IR, alpha and TE as:

$$
\begin{aligned}
IR_{total} &= \frac{\sum \frac{1}{n} \alpha_i}{\left(\sum \left(\frac{1}{n} \right)^2 \sigma_{\alpha_i}^2 \right)^{\frac{1}{2}}} \\
&= \frac{\bar{\alpha}}{\bar{\sigma}_\alpha} n^{\frac{1}{2}}
\end{aligned} \tag{3.30}
$$

We find that as we include more managers or strategies to the consolidated portfolio, the IR_{total} increases, the increase however is diminishing in nature. Investors should carefully consider adding too many active managers as the average alpha in the feasible set is negative and active investing can be considered a zero-sum-game (Sharpe, 1991). Adding additional managers will reduce active risk at the expense of incurring negative alphas from inferior managers. The aim is to identify and include a small number of superior active managers. The arguments in favour of adding managers is specialisation and diversification. Specialisation is expressed in the nominator of equation 3.30 and the aim is to include only additional managers if we believe they can increase the average alpha of the portfolio.

3.4.3 Core-Satellite: What is the Optimal Satellite Allocation?

The active vs passive vs smart-beta allocation problem comes down to the conviction investors have in the satellite component of the portfolio as well as their risk budgets. This can be illustrated using the following simplified example: suppose an IFA has the option to invest client's funds between passive, active, or smart-beta strategies with a *TE* constraint of 2.5 percent for the portfolio. The manager can either hire an active manager with a *TE* of 2.5

percent, or the IFA constructs a portfolio consisting of a passive core of ±80 percent with active and smart-beta satellites amounting to ±20 percent. Let's assume the active and smart-beta blend has a *TE* of 5 percent. The coefficient of risk-aversion with respect to relative risk is $\lambda = 0.1$, then the optimal satellite allocation would be:

$$W_{active,\ smart-beta} = \frac{IR}{2\lambda TE_{active}}$$

$$= \frac{0.5}{2 \times 0.1 \times 5\%}$$

$$= 50\%$$

The resulting $TE_{portfolio} = 5\% \times 50\% = 2.5\%$

3.4.4 Fee & TE Arbitrage with Core-Satellite

"Beating the market is a notoriously tough game to play. Playing it with one hand tied behind one's back does not seem to be a good starting point."

- Amenc, Malaise and Martellini (2004)

We can utilise core-satellite portfolios to track the benchmark index closely *"core"* while allocating a portion to active and smart-beta managers *"satellite"* who we believe will generate significant levels of alpha. In order for active managers to generate positive excess returns, they would need to deviate from their benchmarks, resulting in *TE* which is not necessarily bad. Thus, the idea of *"good"* and *"bad" TE* as highlighted by Amenc, Malaise and Martellini (2004). Allowing the active and smart-beta managers to deviate from their benchmarks gives them the freedom to utilise their skills. We point out that active managers with a 5 percent TE constraint, gives them little room to implement market beating strategies. In addition, core-satellite portfolios provide cost control to the end investor. Fee and *TE* arbitrage can be achieved as follows **(Table 3.1)**. Let's assume the investor has a $TE_{portfolio} = 5\%$ constraint. The investor can allocate 100 percent of their capital to an active manager who adheres to this constraint. The active manager in this case charges a management fee of 110 basis points. Alternatively, the investor can decide to apply the concept of core-satellite portfolio construction and allocate 75 percent of their capital to an index tracking product such as an ETF or index fund and the remaining 25 percent of their capital to high conviction active and smart-beta manager with ±20 percent *TE* constraints. We can assume the cost of the index tracking portion is 20 basis points and due to the specialist nature satellite allocation, the management fee is 130 basis points.

Table 3.1: Fee & TE Arbitrage with Core-Satellite

Core-Satellite			
	"Core"	*"Satellite"*	Core-Satellite
Weight	75%	25%	**100%**
TE	0%	20%	**5%** *(0%x0.75 + 20%x0.25)*
Management Fees	16bps	130bps	**44.5bps** *(16x0.75 + 130x0.25)*
Active Only			
			Active
Weight			**100%**
TE			**5%**
Management Fees			**110bps**

Our research aims to emphasise that using core-satellite portfolios within the risk mandate of the investor will enable the investor to enhance risk budgeting between the core and the satellite as well as determine which portion of the portfolio contributes to *TE*, fees and most importantly, mean-variance efficiency of the consolidated portfolio.

The investor can use core-satellite methods to diversify their portfolios without sacrificing potential alpha that is generated by superior active and smart-beta managers (Amenc, Malaise & Martellini, 2004).

3.5 Returns Based Style Analysis

"An asset class factor model can help make order out of chaos."

- William Sharpe (1992)

Returns Based Style Analysis (RBSA), originally introduced by Sharpe (1988, 1992), is regarded as an invaluable tool and statistical technique than has gained immense popularity among financial advisors, endowments, plan sponsors, investment consultants and potentially the next generation of Robo-advisors. RBSA is used by investors to understand the investment mandate and objective of active fund managers.

The foundation and cornerstone of RBSA evolves around the notion that an active fund manager uses a particular style (i.e. growth, value, low volatility, quality, small cap, large cap or perhaps even geographical styles such as global equity, US equity or European equity) to manage the fund. This study will incorporate RBSA as a secondary filter to eliminate actively managed mutual funds who do not outperform or fail to add value above from the passively managed indices or benchmarks available to South African investors.

RBSA, compared to characteristics-based style analysis (CBSA) does not require portfolio holdings as inputs. CBSA requires actual portfolio holdings, compared to RBSA which uses a time series of historical portfolio returns. As input, RBSA uses a time series of historical return data and compares it to the return characteristics of various passive indices. Thus, comparing the return characteristics of an active manager to the return characterises of several passive benchmarks. RBSA is primarily used to determine whether active fund managers add any value *"alpha"* compared to the passive style factors or benchmark indices they seek to replicate or mimic in their investment approach.

RBSA, as proposed by Sharpe (1992) uses a multi-factor model as expressed by equation 3.31:

$$R_i = [b_{i1}F_1 + b_{i2}F_2 + \cdots + b_{in}F_n] + e_i \tag{3.31}$$

Where

R_i	=	return of unit trust i
F_j	=	return of each benchmark index j
b_{ij}	=	sensitivity of unit trust i to benchmark index j
e_i	=	non-factor component of return on i "error term" interpreted as the in smaple excess return for unit trust i that is not explained by unit trust i exposures to the returns of the benchmark index (i.e. it is the difference between the return of the funds (actual values) and that of a passive portfolio with the same style (fitted values)

Equation 3.31, as originally proposed by Sharpe (1992), has the following constraints:

1. Short selling is prohibited
2. The sensitivity factors have to sum to 1

Sharpe (1992) uses 12 asset classes in his original regression model. These indices were chosen because they could be purchased by investors as a passive strategy which could potentially be added to a consolidated portfolio. These indices were also not active in nature and included; European stocks, Japanese stocks, US large capitalisation value stocks, US large capitalisation growth stocks, US medium capitalisation stocks, US small capitalisation stocks, US treasury bills, Intermediate term US government bonds, Long term US government bonds, US corporate bonds, Mortgage backed securities and non US bonds.

In order to implement RBSA, a specified number of monthly return data for active funds, style factors and benchmarks are required. Traditionally, monthly return data for 24 months to 60 months is used. This study will use 36 months of previous monthly data to determine the style exposure and time series estimation of active funds over any 36 month rolling window period. The output from the 36 month rolling regression is the style exposure of each active fund. This will be used to eliminate active managers who fail to add value compared to the style factors represented by passive benchmarks or building blocks.

More than 80 percent of the variation in an actively manage fund can be explained by either asset class, style indices or a combination of both factors (Sharpe, 1992). RBSA can be applied to multi asset, or more commonly known as balanced funds since approximately 90 percent of the monthly return variation can be attributed to style indices and asset classes.

3.6 Statistical Software Used to Implement Methodology: A-DEX PRISM

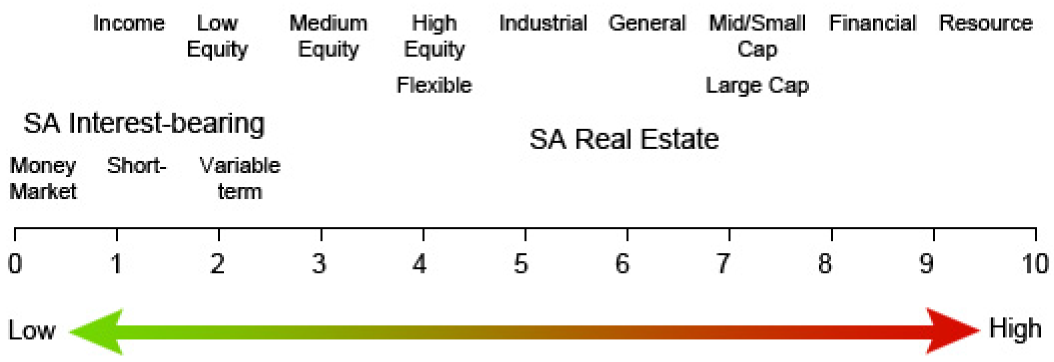
A-DEX PRISM is a cloud-based tool that allows investment professionals and analysts to visualise, design and manage their investment portfolio. The software offers a powerful interactive 3-D graphical interface to allocate multidimensional risk budgets across investments and asset classes, x-ray existing active funds and create optimised portfolios. Potential users are anybody who is a responsible for the allocation of investment funds. A-DEX PRISM is used extensively in this research to implement the methodology discussed in this chapter and eventually develop a range of core-satellite products.

Chapter 4: Data

4.1 Data Overview and Assumptions

The data covered in the study includes active, passive and smart-beta funds that meet the risk classification of PlexCrown (2019) SA Unit Trust Risk Classification Framework as summarised in **Figure 4.1.**

Figure 4.1: PlexCrown SA Unit Trust Risk Classification Framework



Source: PlexCrown (2019)

PlexCrown (2019) classifies SA unit trust funds according to their risk. The data in our study therefore includes the following classifications of funds, forming the product range available to investors:

1. **High Risk: SA Equity General**
2. **Medium Risk: SA Multi-Asset High Equity**
3. **Low Risk: SA Multi-Asset Low Equity**

We use total monthly returns (TR) for CIS funds on the ASISA framework included in the (1) SA Equity General Sector, (2) SA Multi-Asset High Equity Sector and (3) SA Multi-Asset Low Equity Sector for the period **October 2009 – September 2019** which covers **120 months** of TR data. The monthly unit trust and benchmark TR's are obtained from Longboat Analytics using their flagship product, Fund Focus. TR data for ETF's and index funds are also obtained from Fund Focus. The asset allocation frameworks set by ASISA enable us to replicate portfolios that meet their classifications and in turn meet the greater investment objectives of numerous South African investors.

All funds forming part of the analysis are grouped according to their first tier of classification and are South African Portfolios. Therefore, the funds must invest a minimum of 60% of their assets in South Africa. The funds may invest a maximum of 30% of their assets outside of South Africa. 10% of their assets may be invested in Africa excluding South Africa (ASISA, 2018).

4.2 High Risk: SA General Equity Funds

SA general equity funds must invest a minimum of 80% of the market value of the portfolios in equities. These funds have a maximum capital appreciation mandate. The portfolios in this category offer medium to long-term capital growth as their primary investment objective.

- **Standardised Benchmark:** FTSE/JSE All Share index (J203T)

Our research identifies 190 retail general equity funds in SA at 30 June 2019 with a total AUM of R276 269 billion. The largest general equity fund is the Allan Gray Equity Fund with an AUM of R38 724 billion. The mean AUM of general equity funds is R1 723 billion. We use a filtering technique to select equity funds that form part of our analysis. Three AUM brackets are formed for general equity funds. These brackets are:

- Large-sized funds *(R10 billion < AUM < R40 billion),*
- Medium-sized funds *(R5 billion < AUM < R10 billion)*
- Small-sized funds *(R0 billion < AUM < R10 billion)*

Approximately ten of largest funds from each AUM bracket is selected to form part of the sample. The funds must be at least older than four years. These funds are included in the analysis because they are freely available on several well-known LISPs in South Africa, which can be accessed by IFA’s, retail investors and most importantly, Robo-advisors.

Our sample[3] **(Annexure A)** includes **24 SA general equity funds** with a combined AUM of R200 944 billion.

[3] Fairtree Equity Prescient Fund – data only available for (Dec 2011 – Sep 2019).

Abax Equity Prescient Fund – data only available for (Feb 2013 – Sep 2019).

4.3 Medium Risk: SA Multi-Asset High Equity Funds

SA multi-asset high equity funds may allocate capital to a wide range of asset classes including equities, bonds, money market and listed property. These funds exhibit short term volatility, however their aim is to maximise capital growth over the long term. They may therefore invest in up to 75% equites (local and international), however, these funds must meet the SA portfolio criteria of investing at least 60% of their assets in South African markets.

- **Standardised Benchmark:** 75% FTSE/JSE All Share index (J203T) + 25% JSE/ASSA All Bond Index (ALBI). The standardised benchmark was derived using the maximum ASISA Equity allocation of 75%.

Our research identifies 219 retail multi-asset high equity funds in SA at 30 June 2019 with a total AUM of R586 164 billion. The largest multi-asset high equity fund is the Allan Gray Balanced Fund with an AUM of R150 563 billion. The mean AUM of multi-asset high equity funds is R2 677 billion. We use a filtering technique to select multi-asset high equity funds that form part of our analysis. Three AUM brackets are formed for multi-asset high equity funds. These brackets are:

- Large-sized funds *(R20 billion < AUM < R151 billion)*
- Medium-sized funds *(R10 billion < AUM < R20 billion)*
- Small-sized funds *(R2 billion < AUM < R10 billion)*

Approximately ten of largest funds from each AUM bracket is selected to form part of the sample. The funds must be at least older than four years. These funds are included in the analysis because they are freely available on several well-known LISPs in South Africa, which can be accessed by IFA's, retail investors and most importantly, Robo-advisors.

Our sample[4] **(Annexure B)** includes **23 multi-asset high equity funds** with a combined AUM of R497 464 billion.

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[4] Alexander Forbes Investments Performer Managed Unit Trust – data only available for (Feb 2011 – Sep 2019).

PPS Balanced FOF – data only available for (Aug 2011 – Sep 2019).

Sasfin BCI Prudential Fund – data only available for (Feb 2013 – Sep 2019).

Satrix Balanced Index Fund – data only available for (Nov 2013 – Sep 2019).

Sygnia CPI +6% Fund – data only available for (Aug 2012 – Sep 2019).

4.4 Low Risk: SA Multi-Asset Low Equity Funds

SA multi-asset low equity funds may allocate capital to a wide range of asset classes including equities, bonds, money market and listed property. These funds incur low levels of volatility and aim to maximise capital growth over the long term while generating stable income over the short term. They may therefore invest in up to 40% equites (local and international), however, these funds must meet the SA portfolio criteria of investing at least 60% of their assets in South African markets.

- **Standardised Benchmark:** 40% FTSE/JSE All Share index (J203T) + 40% JSE/ASSA All Bond Index (ALBI) + 20% STeFI Composite index. The standardised benchmark was derived using the maximum ASISA Equity allocation of 40%.

Our research identifies 165 retail multi-asset low equity funds in SA at 30 June 2019 with a total AUM of R275 890 billion. The largest multi-asset low equity fund is the Allan Gray Stable Fund with an AUM of R50 867 billion. The mean AUM of multi-asset low equity funds is R1 672 billion. We use a filtering technique to select multi-asset low equity funds that form part of our analysis. Three AUM brackets are formed for multi-asset low equity funds. These brackets are:

- Large-sized funds *(R20 billion < AUM < R55 billion)*
- Medium-sized funds *(R10 billion < AUM < R20 billion)*
- Small-sized funds *(R2 billion < AUM < R10 billion)*

Approximately ten of largest funds from each AUM bracket is selected to form part of the sample. The funds must be at least older than four years. These funds are included in the analysis because they are freely available on several well-known LISPs in South Africa, which can be accessed by IFA's, retail investors and most importantly, Robo-advisors.

Our sample[5] **(Annexure C)** includes **14 multi-asset low equity funds** with a combined AUM of R206 124 billion.

[5] PSG Stable Fund – data only available for (Oct 2011 – Sep 2019).

4.5 Index Funds, ETF's and Benchmarks

TR data for index funds, ETF's and several benchmarks are included in this study. Index funds and ETF's are used along with active and smart-beta funds to form core-satellite portfolios. Benchmarks data is incorporated into the analysis to measure the performance of active, passive and core-satellite portfolios as well as to generate descriptive statistics discussed in the research methodology. A total of **five index funds and ETF's (Annexure D)** are included as passive alternatives along with **seven benchmarks (Annexure E)**.

4.6 Smart-Beta and A-DEX PRISM Funds

Monthly smart-beta TR data for the period **October 2009 – September 2019** are obtained from A-DEX PRISM.

We use the following **three smart-beta funds** in our analysis to form part of our product range:

1. **A-DEX SA Momentum Fund:** Please see **(Annexure F)** for the fund factsheet, along with the fund description and objectives.

2. **A-DEX SA Value Fund:** Please see **(Annexure F)** for the fund factsheet, along with the fund description and objectives.

3. **A-DEX SA Low Volatility Fund:** Please see **(Annexure F)** for the fund factsheet, along with the fund description and objectives.

Chapter 5: Data Analysis, Results and Portfolio Construction

5.1 Portfolio Mandates and Objectives

The primary aim of this study is to replicate portfolios called *“target portfolios”* from ASISA’s framework. By replicating as close as possible the asset allocation and risk profiles of these *“target portfolios”,* we develop a product range of low-cost core-satellite portfolios called *“replica portfolios”* by blending active, passive and fundamental factors.

The risk profiles and *“target portfolios”* identified in this study would typically be included in portfolios of South African investors during several life cycles. The portfolios are classified as South African portfolios and should, therefore, invest at least 60% of their assets in South Africa. These portfolios may invest a maximum of 30% of their assets outside of South Africa (ASISA, 2018).

The risk profiles are:

1. **High Risk: SA Equity General** *(Minimum 80% of the portfolio in equities)*
   Standardised Benchmark: FTSE/JSE All Share Index (J203T) (ASISA, 2018)

2. **Medium Risk: SA Multi-Asset High Equity** *(Maximum 75% of the portfolio in equities)*
   Standardised Benchmark: 75% FTSE/JSE All Share Index (J203T) + 25% JSE/ASSA All Bond Index (ALBI)

3. **Low Risk: SA Multi-Asset Low Equity** *(Maximum 40% of the portfolio in equities)*
   Standardised Benchmark: 40% FTSE/JSE All Share index (J203T) + 40% JSE/ASSA All Bond Index (ALBI) + 20% STeFI Composite index

The active funds included in the study form part of the risk classification of PlexCrown SA Unit Trust Risk Classification framework as summarised in **Figure 4.1.** These risk profiles are included in the fund classification framework of ASISA with a combined AUM of R1 138 trillion as of 30 June 2019. Our sample of 61 active funds has a combined AUM of R904 532 billion as of 30 June 2019. Our sample, therefore, represents 79.46% of all active funds in the above three ASISA categories.

These active funds are the most popular and frequently used by IFA's, retail investors and potentially Robo-advisors. These funds are freely available on several well-known LISPs in South Africa including:

- Allan Gray Investment Platform
- Alexander Forbes Investment Platform
- Glacier (Sanlam)
- Investec iSelect
- Momentum Wealth - Fundshop

Our sample of active funds is a good representation of the most popular active funds that are freely available and easily accessible. They can be used by Robo-advisors to construct low-cost core-satellite portfolios for South African investors using several portfolio optimisation methodologies.

5.2 Replica Portfolio Design

The replica portfolios are designed to expose the investor to a low-cost primary *"core"* consisting of passive and index funds, thus systematic risk *"beta",* limiting the tracking error and cost as measured by TER of the portfolio. The secondary *"satellite"* component of the portfolio is allocated to active and smart-beta managers to exploit expected excess return *"alpha"*. Furthermore, we wish to explore risk budgeting techniques that can be practically implemented to reduce the overall risk, measured by the standard deviation of the portfolio.

The active component of each *"replica portfolio"* will be selected based on funds size as per AUM bracket, Sharpe Ratio, Information Ratio, TE and standard deviation of returns. The passive and smart-beta component will be added to the active component to generate core-satellite portfolios. We wish to determine whether the core-satellite portfolio can outperform the *"target portfolios"* on a risk-adjusted basis.

Moreover, the study explores whether core-satellite portfolios can reduce the overall cost as measure by TIC compared to a purely active managed portfolio.

5.3 Creating the Replica Portfolios – Step 1 Target Portfolio Data Analysis

5.3.1 Results Discussion - SA General Equity Funds

Of the **24 SA general equity** funds included in the analysis, **only one, Fairtree Equity Prescient Fund,** managed to outperform the benchmark (FTSE/JSE All Share (J203T)), on an absolute basis over the sample period. The average return for large-sized SA general equity funds was 10.01 percent per annum, medium-sized SA general equity funds generated 9.08 percent per annum, while small-sized SA general equity funds generated an average return of 9.03 percent per annum. The return of the benchmark was 12.43 percent per annum over the sample period.

23 of the 24 SA general equity funds exhibited less risk, measured by the standard deviation of annual returns compared to the benchmark (FTSE/JSE All Share (J203T)). **Investec Value Fund** had a total risk of 18.69 percent per annum, compared to 13.06 percent total risk per annum of the benchmark (FTSE/JSE All Share (J203T)). The average risk incurred by large-sized SA general equity funds was 11.39 percent per annum, medium-sized SA general equity funds had a lower standard deviation of 10.73 percent per annum, while small-sized SA general equity funds had an average standard deviation of 11.42 percent per annum.

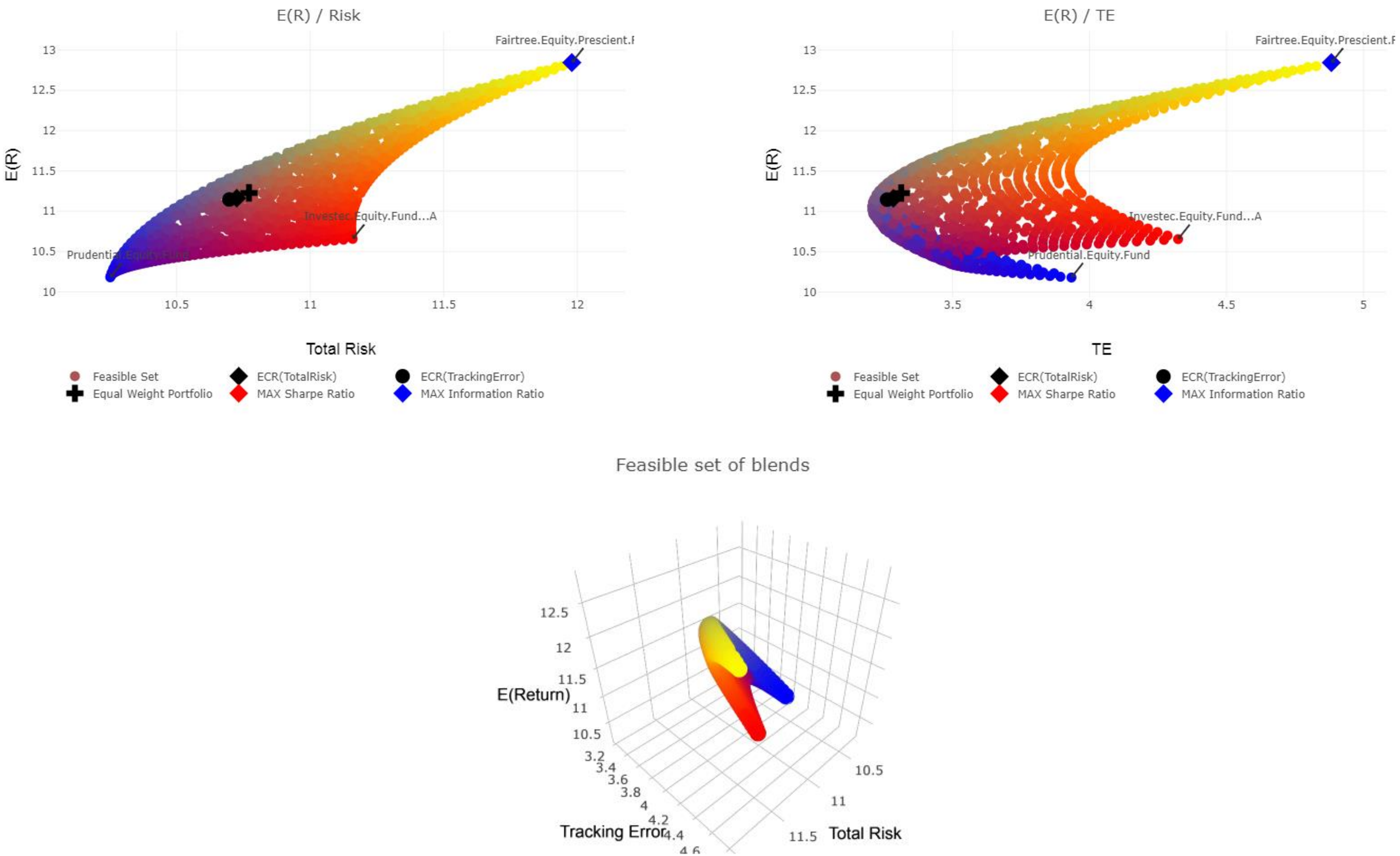
The average tracking error for large-sized SA general equity funds was 4.66 percent per annum, medium-sized SA general equity funds had an average tracking error of 4.66 percent per annum, while small-sized SA general equity funds had an average tracking error of 6.76 percent per annum.

Assigning a score to the Sharpe and Information Ratio of each SA general equity fund, we can rank each fund **(Table 5.1)**. A lower score represents a superior ratio, while a higher score indicates that the manager was not compensated for taking risks or deviating from the benchmark. **Fairtree Equity Prescient Fund** scored one for both the Sharpe (0.53) and Information Ratio (2.61), with a total score of two, the fund is classified as the best large-sized SA general equity fund. **Investec Equity Fund** scored one for the Sharpe (0.43) and two for the Information Ratio (2.78), with a total score of three, the fund is classified as the best medium-sized SA general equity fund. **Prudential Equity Fund** scored two for the Sharpe (0.43) and one for the Information Ratio (2.87), with a total score of three, the fund is classified as the best small-sized SA general equity fund.

Table 5.1: Target Portfolio Results - SA General Equity Funds

SA General Equity Funds *(10 Billion < ZAR < 40 Billion) ~ 6 funds*								
FUND	**Total Return (% p.a.)**	**Total Risk (% p.a.)**	**Tracking Error (% p.a.)**	**Sharpe Ratio**	**Score**	**Information Ratio**	**Score**	**Total**
Allan Gray Equity Fund	10.76	10.00	5.10	0.42	2	2.09	4	6
Coronation Top 20 Fund	11.05	12.87	5.18	0.35	3	2.11	3	6
Old Mutual Investors Fund	9.57	11.24	3.96	0.27	4	2.39	2	6
Fairtree Equity Prescient Fund	12.84	11.98	4.88	0.53	1	2.61	1	2
Nedgroup Investments Rainmaker Fund	8.57	10.99	4.59	0.19	5	1.84	5	10
Abax Equity Prescient Fund	7.25	11.24	4.22	0.07	6	1.69	6	12
Average	**10.01**	**11.39**	**4.66**	**0.31**		**2.12**		
Benchmark (FTSE/JSE All Share (J203T))	12.43	13.06		0.45				
SA General Equity Funds *(5 Billion < ZAR < 10 Billion) ~ 8 funds*								
FUND	**Total Return (% p.a.)**	**Total Risk (% p.a.)**	**Tracking Error (% p.a.)**	**Sharpe Ratio**	**Score**	**Information Ratio**	**Score**	**Total**
Stanlib Multi-Manager Equity Fund	7.87	10.44	3.91	0.13	5	1.98	4	9
Investec Equity Fund	11.49	11.49	4.09	0.43	1	2.78	2	3
PSG Wealth Creator FOF	9.20	10.15	5.39	0.27	4	1.68	6	10
Sanlam (SIM) General Equity Fund	10.62	11.12	3.72	0.37	2	2.82	1	3
Coronation Equity Fund	11.57	11.66	4.17	0.43	1	2.74	3	4
Foord Equity Fund	10.24	11.24	5.26	0.33	3	1.92	5	8
Oasis Crescent Equity Fund	7.43	9.27	7.02	0.10	6	1.04	8	14
PortfolioMetrix BCI Equity FOF	4.19	10.47	3.73	-0.22	7	1.09	7	14
Average	**9.08**	**10.73**	**4.66**	**0.23**		**2.01**		
Benchmark (FTSE/JSE All Share (J203T))	12.43	13.06		0.45				
SA General Equity Funds *(0 Billion < ZAR < 5 Billion) ~ 10 funds*								
FUND	**Total Return (% p.a.)**	**Total Risk (% p.a.)**	**Tracking Error (% p.a.)**	**Sharpe Ratio**	**Score**	**Information Ratio**	**Score**	**Total**
PSG Equity Fund	11.12	11.23	8.24	0.41	3	1.33	7	10
Prudential Dividend Maximiser Fund	10.79	10.60	4.14	0.40	4	2.58	2	6
Stanlib Equity Fund	10.67	10.31	5.67	0.40	4	1.86	4	8
Investec Value Fund	8.51	18.69	17.28	0.11	7	0.49	10	17
Marriott Dividend Growth Fund	11.65	9.73	8.49	0.53	1	1.36	6	7
Prudential Equity Fund	11.20	10.99	3.86	0.43	2	2.87	1	3
Allan Gray SA Equity Fund	2.97	10.85	4.59	-0.33	9	0.62	9	18
Stanlib SA Equity Fund	7.88	11.36	4.75	0.12	6	1.63	5	11
Discovery Equity Fund	6.79	9.97	6.40	0.03	8	1.04	8	16
Absa Select Equity Fund	8.72	10.48	4.21	0.21	5	2.04	3	8
Average	**9.03**	**11.42**	**6.76**	**0.23**		**1.58**		
Benchmark (FTSE/JSE All Share (J203T))	12.43	13.06		0.45				

Figure 5.1: Target Portfolio Results – Best SA General Equity Funds



5.3.2 Results Discussion - SA Multi-Asset High Equity Funds

Of the **23 SA multi-asset high equity** funds included in the analysis, **only one, Rezco Value Trend Fund** managed to outperform the benchmark (75% FTSE/JSE All Share index (J203T) + 25% JSE/ASSA All Bond Index (ALBI)), on an absolute basis over the sample period. The average return for large-sized SA multi-asset high equity funds was 10.15 percent per annum, medium-sized SA multi-asset high equity funds generated 9.67 percent per annum, while small-sized SA multi-asset high equity funds generated an average return of 8.76 percent per annum. The return of the benchmark was 11.49 percent per annum over the sample period.

All SA multi-asset high equity funds included in the analysis exhibited less risk, measured by the standard deviation of annual returns compared to the benchmark (75% FTSE/JSE All Share index (J203T) + 25% JSE/ASSA All Bond Index (ALBI)). The average risk incurred by large-sized SA multi-asset high equity funds was 7.22 percent per annum, medium-sized SA multi-asset high equity funds had a lower standard deviation of 6.88 percent per annum, while small-sized SA multi-asset high equity funds had an average standard deviation of 6.97 percent per annum. The risk of the benchmark over the sample period was 10.76 percent per annum.

The average tracking error for large-sized SA multi-asset high equity funds was 5.73 percent per annum, medium-sized SA multi-asset high equity funds had an average tracking error of 5.58 percent per annum, while small-sized SA multi-asset high equity funds had an average tracking error of 5.29 percent per annum.

Assigning a score to the Sharpe and Information Ratio of each SA multi-asset high equity fund, we are able to rank each fund **(Table 5.2)**. **Prudential Balanced Fund** scored one for both the Sharpe (0.56) and Information Ratio (2.46), with a total score of two, the fund is classified as the best large-sized SA multi-asset high equity fund. **Investec Managed Fund** scored one for the Sharpe (0.68) and two for the Information Ratio (1.84), with a total score of three, the fund is classified as the best medium-sized SA multi-asset high equity fund. **Stanlib Multi-Manager Balanced Fund** scored four for the Sharpe (0.36) and two for the Information Ratio (1.91), with a total score of six, the fund is classified as the best small-sized SA multi-asset high equity fund.

Table 5.2: Target Portfolio Results - SA Multi-Asset High Equity Funds

SA Multi-Asset High Equity Funds ***(20 Billion < ZAR < 151 Billion) ~ 7 funds***

FUND	Total Return (% p.a.)	Total Risk (% p.a.)	Tracking Error (% p.a.)	Sharpe Ratio	Score	Information Ratio	Score	Total
Allan Gray Balanced Fund	10.18	6.85	6.72	0.54	2	1.50	6	8
Coronation Balanced Plus Fund	10.53	7.84	5.30	0.51	4	1.97	3	7
Investec Opportunity Fund	9.85	6.32	6.55	0.53	3	1.49	7	10
Foord Balanced Fund	10.12	7.79	6.09	0.46	5	1.64	4	9
Discovery Balanced Fund	10.46	7.48	5.11	0.53	3	2.02	2	5
Prudential Balanced Fund	10.78	7.64	4.34	0.56	1	2.46	1	2
PSG Wealth Moderate FOF	9.10	6.60	5.97	0.39	6	1.51	5	11
Average	**10.15**	**7.22**	**5.73**	**0.50**		**1.80**		
Benchmark (75% FTSE/JSE + 25% ALBI)	11.49	10.76						

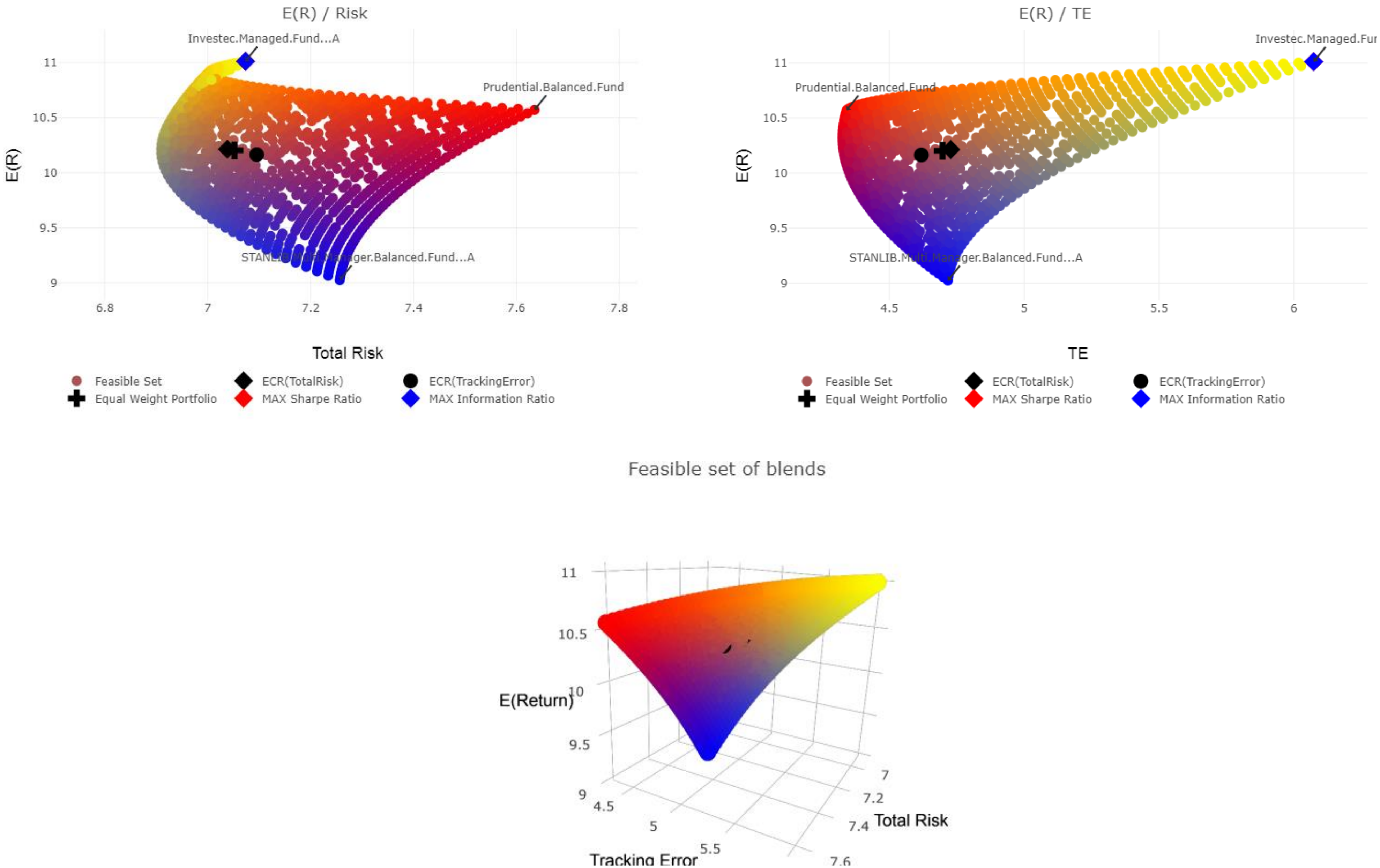
SA Multi-Asset High Equity Funds ***(10 Billion < ZAR < 20 Billion) ~ 5 funds***

FUND	Total Return (% p.a.)	Total Risk (% p.a.)	Tracking Error (% p.a.)	Sharpe Ratio	Score	Information Ratio	Score	Total
Sanlam (SIM) Balanced Fund	9.45	7.20	4.46	0.41	3	2.09	1	4
Old Mutual Balanced Fund	8.86	7.10	4.86	0.33	5	1.80	3	8
Investec Managed Fund	11.31	7.07	6.07	0.68	1	1.84	2	3
Old Mutual Multi-Managers Balanced FOF	8.82	6.61	5.29	0.35	4	1.65	4	8
PSG Balanced Fund	9.92	6.42	7.22	0.53	2	1.36	5	7
Average	**9.67**	**6.88**	**5.58**	**0.46**		**1.75**		
Benchmark (75% FTSE/JSE + 25% ALBI)	11.49	10.76						

SA Multi-Asset High Equity Funds ***(2 Billion < ZAR < 10 Billion) ~ 11 funds***

FUND	Total Return (% p.a.)	Total Risk (% p.a.)	Tracking Error (% p.a.)	Sharpe Ratio	Score	Information Ratio	Score	Total
Stanlib Multi-Manager Balanced Fund	9.13	7.26	4.72	0.36	4	1.91	2	6
Rezco Value Trend Fund	11.50	7.49	7.91	0.67	1	1.44	9	10
Satrix Balanced Index Fund	6.94	7.31	3.76	0.06	11	1.82	4	15
Stanlib Balanced Fund	9.43	7.05	5.33	0.41	3	1.75	6	9
Marriott Balanced FOF	9.09	5.22	6.97	0.49	2	1.29	10	12
Sanlam Multi-Managed Balanced FOF	8.94	7.00	4.69	0.35	5	1.88	3	8
Alexander Forbes Performer Managed UT	8.87	7.01	4.22	0.34	6	2.07	1	7
Sasfin BCI Prudential Fund	7.22	6.91	5.64	0.10	10	1.26	11	21
Sygnia CPI +6% Fund	8.88	7.27	4.85	0.33	7	1.81	5	12
PPS Balanced FOF	8.22	7.10	4.81	0.24	8	1.69	7	15
Absa Multi-Managed Growth FOF	8.14	7.08	5.34	0.23	9	1.50	8	17
Average	**8.76**	**6.97**	**5.29**	**0.33**		**1.67**		
Benchmark (75% FTSE/JSE + 25% ALBI)	11.49	10.76						

Figure 5.2: Target Portfolio Results – Best SA Multi-Asset High Equity Funds



5.3.3 Results Discussion - SA Multi-Asset Low Equity Funds

Of the **14 SA multi-asset low equity** funds included in the analysis, **not one** fund managed to outperform the benchmark (40% FTSE/JSE All Share index (J203T) + 40% JSE/ASSA All Bond Index (ALBI) + 20% STeFI Composite index), on an absolute basis over the sample period. The average return for large-sized SA multi-asset low equity funds was 9.14 percent per annum, medium-sized SA multi-asset low equity funds generated 8.42 percent per annum, while small-sized SA multi-asset low equity funds generated an average return of 8.28 percent per annum. The return of the benchmark was 9.80 percent per annum over the sample period.

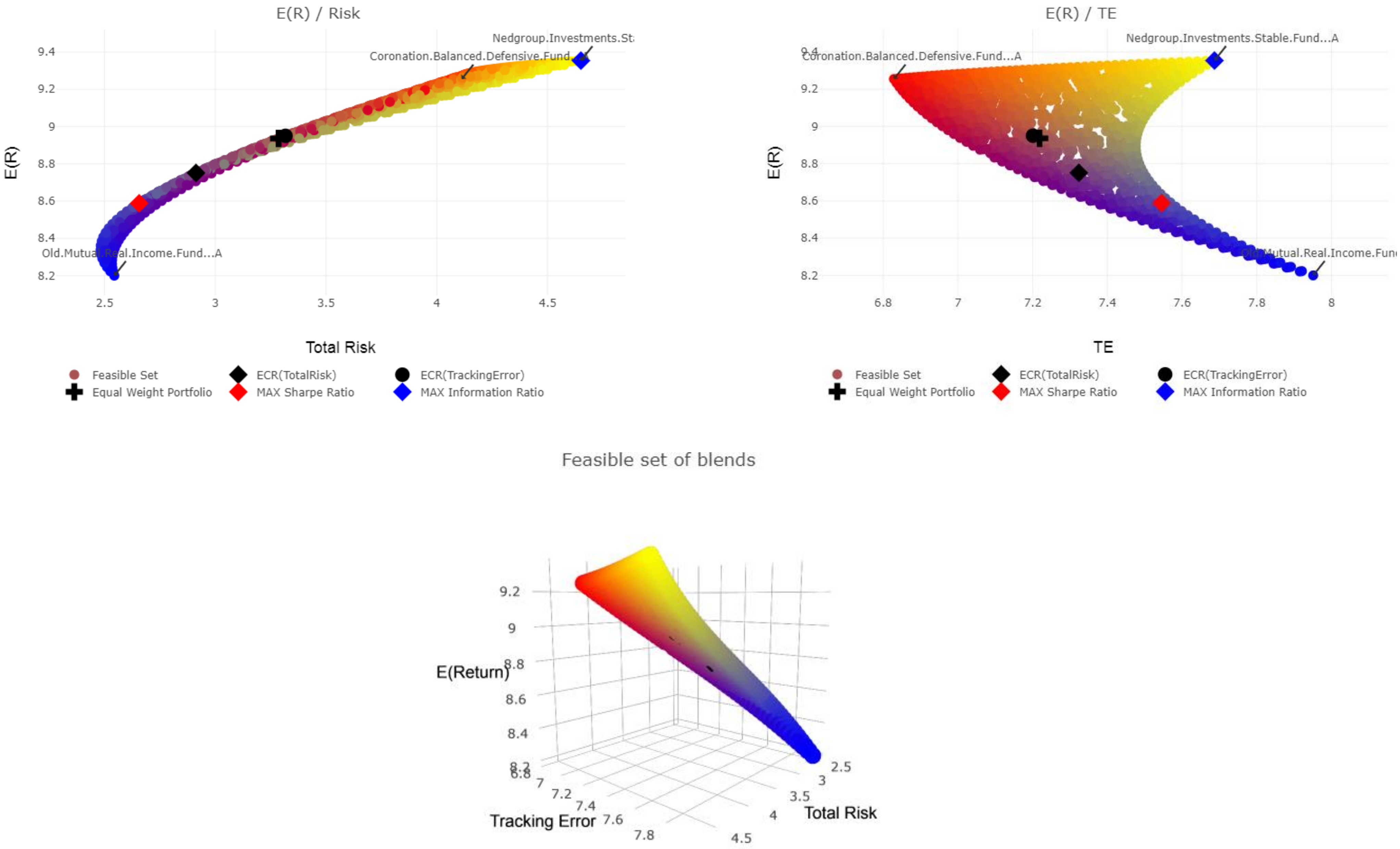
All SA multi-asset low equity funds included in the analysis exhibited less risk, measured by the standard deviation of annual returns compared to the benchmark. The average risk incurred by large-sized SA multi-asset low equity funds was 4.64 percent per annum, medium-sized SA multi-asset low equity funds had a lower standard deviation of 4.03 percent per annum, while small-sized SA multi-asset low equity funds had the lowest average standard deviation of 3.77 percent per annum. The risk of the benchmark over the sample period was 7.01 percent per annum. The average tracking error for large-sized SA multi-asset low equity funds was 5.32 percent per annum. Medium-sized SA multi-asset low equity funds had an average tracking error of 5.44 percent per annum, while small-sized SA multi-asset low equity funds had an average tracking error of 4.42 percent per annum.

Assigning a score to the Sharpe and Information Ratio of each SA multi-asset low equity fund, we are able to rank each fund **(Table 5.3)**. **Coronation Balanced Defensive Fund** scored one for the Sharpe (0.74) and two for the Information Ratio (2.07), with a total score of three. Also, with a score of three, is Prudential Inflation Plus Fund. However, **Coronation Balanced Defensive Fund** has a higher annualised tracking error, which means an investor holding the fund plus the benchmark will be more diversified. Thus, it is the most attractive large-sized SA multi-asset low equity fund. **Nedgroup Investments Stable Fund** scored one for both the Sharpe (0.68) and the Information Ratio (1.65), with a total score of two, the fund is classified as the best medium-sized SA multi-asset low equity fund. **Old Mutual Real Income Fund** scored one for the Sharpe (0.78) and three for the Information Ratio (1.91), with a total score of four. Also, with a score of four, is Old Mutual Stable Growth Fund. However, **Old Mutual Real Income Fund** has a higher annualised tracking error, which means an investor holding the fund plus the benchmark will be more diversified. Thus, it is the most attractive small-sized SA multi-asset low equity fund.

Table 5.3: Target Portfolio Results - SA Multi-Asset Low Equity Funds

SA Multi-Asset Low Equity Funds *(20 Billion < ZAR < 55 Billion) ~ 3 funds*								
FUND	**Total Return (% p.a.)**	**Total Risk (% p.a.)**	**Tracking Error (% p.a.)**	**Sharpe Ratio**	**Score**	**Information Ratio**	**Score**	**Total**
Allan Gray Stable Fund	8.36	4.71	7.52	0.39	3	1.10	3	6
Coronation Balanced Defensive Fund	9.57	4.11	4.57	0.74	1	2.07	2	3
Prudential Inflation Plus Fund	9.50	5.10	3.87	0.59	2	2.43	1	3
Average	**9.14**	**4.64**	**5.32**	**0.57**		**1.87**		
Benchmark (40% FTSE/JSE + 40% ALBI + 20% STeFI)	9.80	7.01		0.48				
SA Multi-Asset Low Equity Funds *(10 Billion < ZAR < 20 Billion) ~ 4 funds*								
FUND	**Total Return (% p.a.)**	**Total Risk (% p.a.)**	**Tracking Error (% p.a.)**	**Sharpe Ratio**	**Score**	**Information Ratio**	**Score**	**Total**
Nedgroup Investments Stable Fund	9.65	4.65	5.79	0.68	1	1.65	1	2
Sanlam (SIM) Inflation Plus Fund	7.97	3.60	5.00	0.41	3	1.57	2	5
PSG Wealth Preserver FOF	7.74	3.85	4.93	0.32	4	1.55	3	7
Investec Cautious Managed Fund	8.32	4.02	6.03	0.45	2	1.36	4	6
Average	**8.42**	**4.03**	**5.44**	**0.47**		**1.53**		
Benchmark (40% FTSE/JSE + 40% ALBI + 20% STeFI)	9.80	7.01		0.48				
SA Multi-Asset Low Equity Funds *(2 Billion < ZAR < 10 Billion) ~ 7 funds*								
FUND	**Total Return (% p.a.)**	**Total Risk (% p.a.)**	**Tracking Error (% p.a.)**	**Sharpe Ratio**	**Score**	**Information Ratio**	**Score**	**Total**
Stanlib Balanced Cautious Fund	8.10	3.84	4.36	0.41	4	1.84	5	9
Old Mutual Stable Growth Fund	8.20	3.71	4.01	0.46	3	2.02	1	4
Absa Absolute Fund	7.80	3.31	4.28	0.39	5	1.80	6	11
Old Mutual Real Income Fund	8.48	2.54	4.38	0.78	1	1.91	3	4
PSG Stable Fund	8.10	3.48	4.97	0.46	3	1.61	7	10
Absa Multi-Managed Preserver FOF	7.79	4.55	4.00	0.28	6	1.92	2	8
Personal Trust Conservative Managed Fund	9.48	4.98	4.96	0.60	2	1.89	4	6
Average	**8.28**	**3.77**	**4.42**	**0.48**		**1.86**		
Benchmark (40% FTSE/JSE + 40% ALBI + 20% STeFI)	9.80	7.01		0.48				

Figure 5.3: Target Portfolio Results – Best SA Multi-Asset Low Equity Funds



5.4 Creating the Replica Portfolios – Step 2 Elimination using RBSA

The second step in designing the replica portfolios that will form part of the Robo-advisor product range is to use the Sharpe and Information Ratio results **(Table 5.1, 5.2 and 5.3)** from the active "target portfolios". We wish to identify the best active manager per risk profile using RBSA. This step will use RBSA as a secondary filter to eliminate actively managed mutual funds who do not outperform or fail to add value above from the passively managed indices or benchmarks available to South African investors. The following funds were identified as the best active funds per AUM bracket according to their Sharpe and Information Ratios:

1. **High Risk: SA General Equity**

- Large sized SA general equity: Fairtree Equity Prescient Fund
- Medium sized SA general equity: Investec Equity Fund
- Small sized SA general equity: Prudential Equity Fund

2. **Medium Risk: SA Multi-Asset High Equity**

- Large sized SA multi-asset high equity: Prudential Balanced Fund
- Medium sized SA multi-asset high equity: Investec Managed Fund
- Small sized SA multi-asset high equity: Stanlib Multi-Manager Balanced Fund

3. **Low Risk: SA Multi-Asset Low Equity**

- Large sized SA multi-asset low equity: Coronation Balanced Defensive Fund
- Medium sized SA multi-asset low equity: Nedgroup Investments Stable Fund
- Small sized SA multi-asset low equity: Old Mutual Real Income Fund

The analysis utilises A-DEX PRISM and the X-RAY function, which uses RBSA as originally introduced by Sharpe (1988, 1992). The above active funds are analysed while passive asset classes and style indices are used as building blocks. A rolling period of 36 months is used and the aim of the analysis is to identify the optimal weights that best fit the passive asset classes and style indices over the period that has the lowest tracking error to the return of the active fund. A *"Shadow Fund"* is created for the optimal fit for each active fund. We evaluate the return of the active fund versus the return of the *"Shadow Fund"*. The cumulative difference in returns is called *"Manager Selection Returns*, which generates the unique alpha that active managers add over and above the passive asset classes and style indices. Active managers that produce alpha should be considered to form part of the core-satellite Robo-advisor product range. The following asset classes and style indices are used in the RBSA:

1. **High Risk: SA General Equity**

- FTSE/JSE All Share (J203T)
- MSCI AC World (ZAR TR)
- A-DEX SA Momentum Factor
- A-DEX SA Value Factor
- A-DEX SA Low Volatility Factor

2. **Medium Risk: SA Multi-Asset High Equity**

- FTSE/JSE All Share (J203T)
- MSCI AC World (ZAR TR)
- ALBI Total Return - Beassa (ALBI)
- A-DEX SA Momentum Factor
- A-DEX SA Value Factor
- A-DEX SA Low Volatility Factor

3. **Low Risk: SA Multi-Asset Low Equity**

- FTSE/JSE All Share (J203T)
- MSCI AC World (ZAR TR)
- ALBI Total Return - Beassa (ALBI)
- STEFI Composite Index (STFIND)
- A-DEX SA Momentum Factor
- A-DEX SA Value Factor
- A-DEX SA Low Volatility Factor

5.4.1 RBSA Results High Risk: SA General Equity

Table 5.4: Fairtree Equity Prescient Fund X-RAY Results

X-RAY Results of Fairtree Equity Prescient Fund (1 Nov 2014 - 1 Sep 2019)			
	Annualised Return (%)	**Annualised Std Dev (%)**	**Annualised Sharpe Ratio**
Fairtree Equity Prescient Fund	6.87	13.08	0.53
Shadow Fund	6.98	11.03	0.63
Fund to Benchmark	1.61	5.48	**0.29**
Fund to Shadow	-0.11	5.33	**0.00**
FTSE/JSE All Share (J203T)	5.26	11.4	0.46
MSCI AC World (ZAR TR)	14.58	15.74	0.93
Momentum	4.14	12.33	0.34
Low Volatility	3.18	9.9	0.32
Value	9.87	13.39	0.74
Summary and Correlations Results of Fairtree Equity Prescient Fund			
Fund to Shadow		**Fund to Benchmark**	
Alpha (% p.a.)	**-0.01**	Alpha (% p.a.)	2.47
R-Squared	**0.84**	R-Squared	0.83
Correlation	0.92	Correlation	0.91
Tracking Error (% p.a.)	5.33	Tracking Error (% p.a.)	4.88

From the X-RAY results of Fairtree Equity Prescient Fund **(Table 5.4 and Figure 5.4)**, we find that the fund outperforms the benchmark (FTSE/JSE All Share (J203T)) on an absolute basis over the period 1 November 2014 – 1 September 2019. Fairtree Equity Prescient Fund also outperforms the benchmark (FTSE/JSE All Share (J203T)) on a risk-adjusted basis as the annualised Sharpe Ratio of the fund is 0.53, compared to the annualised Sharpe Ratio of the FTSE/JSE All Share (J203T) of 0.46.

Comparing Fairtree Equity Prescient Fund to its shadow fund, which consists out of the following passive asset classes and style indices: **92% FTSE/JSE All Share, 2.50% MSCI World Equity** and **5.50% Value**, the fund fails to outperform on an absolute and risk-adjusted basis. The majority of the variations of returns of Fairtree Equity Prescient Fund can be explained by the holdings of the shadow fund, since the R-squared is 0.84.

The annualised alpha of Fairtree Equity Prescient Fund versus the shadow fund is -0.01, which means the fund slightly failed to add value over the passive asset classes and style indices it seeks to replicate.

5.4.2 RBSA Results Medium Risk: SA Multi-Asset High Equity

Table 5.5: Investec Managed Fund X-RAY Results

X-RAY Results of Investec Managed Fund (1 Sep 2012 – 1 Sep 2019)			
	Annualised Return (%)	**Annualised Std Dev (%)**	**Annualised Sharpe Ratio**
Investec Managed Fund	10.16	6.94	1.46
Shadow Fund	13.37	6.82	1.96
Fund to Benchmark	2.14	3.4	**0.58**
Fund to Shadow	-3.21	3.71	**-0.79**
Benchmark (SA High Equity UT)	8.02	6.46	1.24
FTSE/JSE All Share (J203T)	10.25	11.2	0.92
MSCI AC World (ZAR TR)	18.92	14.63	1.29
ALBI	7.34	7.56	0.97
Momentum	12.89	11.6	1.11
Low Volatility	10.07	9.85	1.02
Value	15.95	12.75	1.25
Summary and Correlations Results of Investec Managed Fund			
Fund to Shadow		**Fund to Benchmark**	
Alpha (% p.a.)	**-2.92**	Alpha (% p.a.)	2.46
R-Squared	**0.73**	R-Squared	0.75
Correlation	0.85	Correlation	0.86
Tracking Error (% p.a.)	3.71	Tracking Error (% p.a.)	3.58

From the X-RAY results of Investec Managed Fund **(Table 5.5 and Figure 5.5)**, we find that the fund outperforms the benchmark (SA High Equity UT Sector) on an absolute basis over the period 1 September 2012 – 1 September 2019. Investec Managed Fund also outperforms the benchmark (SA High Equity UT Sector) on a risk-adjusted basis as the annualised Sharpe Ratio of the fund is 1.46, compared to the annualised Sharpe Ratio of the SA High Equity UT Sector of 1.24. Comparing Investec Managed Fund to its shadow fund, which consists out of the following passive asset classes and style indices: **21.5% FTSE/JSE All Share, 25% ALBI, 35.5% MSCI World Equity, 2% Value,** and **16% Low Volatility**, the fund fails to outperform on an absolute and risk-adjusted basis. A large portion of the variations of returns of Investec Managed Fund can be explained by the holdings of the shadow fund since the R-squared is 0.73. This is, however, significantly less than the R-squared of Prudential Balanced Fund. The annualised alpha of Investec Managed Fund versus the shadow fund is -2.92%, which indicates the fund failed to add value over the passive asset classes and style indices it seeks to replicate. Investec Managed Fund, compared to Prudential Balanced Fund is, however more likely to outperform the passive asset classes and style indices it seeks to replicate.

5.4.3 RBSA Results Low Risk: SA Multi-Asset Low Equity

Table 5.6: Old Mutual Real Income Fund X-RAY Results

X-RAY Results of Old Mutual Real Income Fund (1 Sep 2012 – 1 Sep 2019)			
	Annualised Return (%)	**Annualised Std Dev (%)**	**Annualised Sharpe Ratio**
Old Mutual Real Income Fund	7.17	2.5	2.87
Shadow Fund	8.36	2.53	3.3
Fund to Benchmark	-0.01	3.45	**-0.03**
Fund to Shadow	-1.19	1.82	**-0.62**
Benchmark (SA Low Equity UT)	7.18	4.03	1.78
FTSE/JSE All Share (J203T)	10.25	11.2	0.92
MSCI AC World (ZAR TR)	18.92	14.63	1.29
ALBI	7.34	7.56	0.97
STEFI	6.6	0.26	25.66
Momentum	12.89	11.6	1.11
Low Volatility	10.07	9.85	1.02
Value	15.95	12.75	1.25

Summary and Correlations Results of Old Mutual Real Income Fund			
Fund to Shadow		**Fund to Benchmark**	
Alpha (% p.a.)	**-1.12**	Alpha (% p.a.)	0.51
R-Squared	**0.54**	R-Squared	0.32
Correlation	0.74	Correlation	0.57
Tracking Error (% p.a.)	1.82	Tracking Error (% p.a.)	3.08

From the X-RAY results of Old Mutual Real Income Fund **(Table 5.6 and Figure 5.6)**, we find that the fund slightly underperforms the benchmark (SA Low Equity Sector) on an absolute basis over the period 1 Sep 2012 – 1 Sep 2019. Old Mutual Real Income Fund, however, outperforms the benchmark on a risk-adjusted basis as the annualised Sharpe Ratio of the fund is 2.87, compared to the annualised Sharpe Ratio of the SA Low Equity UT Sector of 1.78. Comparing Old Mutual Real Income Fund to its shadow fund, which consists out of the following passive asset classes and style indices: **12.5% ALBI, 80.5% STEFI, 0.5% MSCI World Equity, 3% Low Volatility and 3.5% Momentum**, the fund fails to outperform on an absolute and risk-adjusted basis. A moderate amount of the variations of returns of Old Mutual Real Income Fund can be explained by the holdings of the shadow fund, since the R-squared is 0.54. The annualised alpha of Old Mutual Real Income Fund versus the shadow fund is -1.12%. However, the R-squared of Old Mutual Real Income Fund is significantly less than its counterparts, it indicates the manager includes alternative asset classes to generate returns over and above the passive asset classes and style indices it seeks to replicate.

5.5 Results and Conclusion – Returns Based Style Analysis and X-RAYS

The results of the RBSA and X-RAYS of the three high-risk SA general equity funds, three medium-risk SA multi-asset high equity funds and three low-risk SA multi-asset low equity funds will be discussed in this section. The results will determine which active fund from each risk category will be included as the active component that will form part of the core-satellite product range. The active funds that manage to add the most value *"alpha"* over and above the passive asset classes and style indices they seek to replicate will be considered. Alternatively, active funds that can generate returns while taking less risk, along with a low correlation and low coefficient of determination compared to its benchmark and shadow fund will be considered. These metrics indicate the manager has the ability to generate returns while taking less risk as well as being agnostic of the composition of its benchmark or competitors.

5.5.1 Conclusion - High Risk: SA General Equity

The three funds from this risk profile that were shortlisted include: (1) Fairtree Equity Prescient Fund, (2) Investec Equity Fund and (3) Prudential Equity Fund.

Fairtree Equity Prescient Fund generated -0.01% alpha per annum versus its shadow fund and 2.47% alpha per annum versus its benchmark **(Table 5.4 and Figure 5.4)**. The average alpha versus shadow fund for this risk profile is -1.35% per annum, while the average alpha versus benchmark is 0.63% per annum. Fairtree Equity Prescient Fund had an R-squared of 0.84 and a correlation of 0.92 to its shadow fund. What is most notable from the X-RAY of the fund **(Figure 5.4)** is that more than 90% of its style is attributed to the FTSE/JSE All Share (J203T). This is significantly higher than the 77.5% FTSE/JSE All Share (J203T) component of Investec Equity Fund **(Annexure G)** and the 67% FTSE/JSE All Share (J203T) component of Prudential Equity Fund **(Annexure H)**. Moreover, Fairtree Equity Prescient Fund's X-RAY indicates 2.5% of the fund's style is attributed to MSCI World Equity, which is significantly lower than the 21.5% and 20% MSCI World Equity style found in Investec Equity Fund and Prudential Equity Fund respectively. **Fairtree Equity Prescient Fund** is therefore selected to form part of the SA general equity core-satellite portfolio because the manager focuses on investing in the South African equity market, where it has a competitive advantage. The fund exhibits a value bias. Therefore, blending the fund with low volatility and momentum styles would be beneficial to the end investor.

5.5.2 Conclusion – Medium Risk: SA Multi-Asset High Equity

The three funds from this risk profile that were shortlisted include: (1) Prudential Balanced Fund, (2) Investec Managed Fund and (3) Stanlib Multi-Manager Balanced Fund.

Investec Managed Fund generated -2.92% alpha per annum versus its shadow fund and 2.46% alpha per annum versus its benchmark **(Table 5.5 and Figure 5.5)**. The average alpha versus shadow fund for this risk profile is -3.34% per annum, while the average alpha versus benchmark is 1.60% per annum. Investec Managed Fund has an R-squared of 0.73 and a correlation of 0.85 to its shadow fund. This is significantly less than the R-squared of Prudential Balanced Fund and Stanlib Multi-Manager Balanced Fund, which is 0.90 and 0.88 respectively. Their correlation to shadow fund is 0.95 and 0.94, respectively.

What is most notable from the X-RAY of Investec Managed Fund **(Table 5.5 and Figure 5.5)** is that 35.5% of its style is attributed to MSCI World Equity. This is materially higher than the 24% MSCI World Equity component of Prudential Balanced Fund **(Annexure I)** and the 29% MSCI World Equity component of Stanlib Multi Manager Balanced Fund **(Annexure J)**. The standard deviation of MSCI World Equity is 14.63% per annum, making it the riskiest component of the passive asset classes and style indices that form part of these funds. Although MSCI World Equity is the most significant contributor to the style of Investec Managed Fund, the fund has an annualised standard deviation of 6.94%, which is less than that of Prudential Balanced Fund **(Annexure I)** and Stanlib Multi Manager Balanced Fund **(Annexure J)** of 7.42% and 7.36 respectively. The annualised return of MSCI World Equity for the period 1 September 2012 – 1 September 2019 in ZAR is 18.92%, making it the best performing style index active managers can include in their portfolios.

Investec Managed Fund is selected to form part of the SA multi-asset high equity core-satellite portfolio since the manager includes a large portion of global equities to the fund while minimising the total risk of the fund. This indicates the manager has the skill to reduce total risk while not sacrificing returns. Also, Investec Managed Fund has a lower R-squared and correlation to its shadow fund compared to its peers. This indicates that the manager has the ability and skill to identify and include alternative asset classes to generate returns, which justifies its active management fees. The fund exhibits a low volatility bias which is common among medium risk funds. Therefore, blending the fund with value and momentum styles would be beneficial to the end investor.

5.5.3 Conclusion – Low Risk: SA Multi-Asset Low Equity

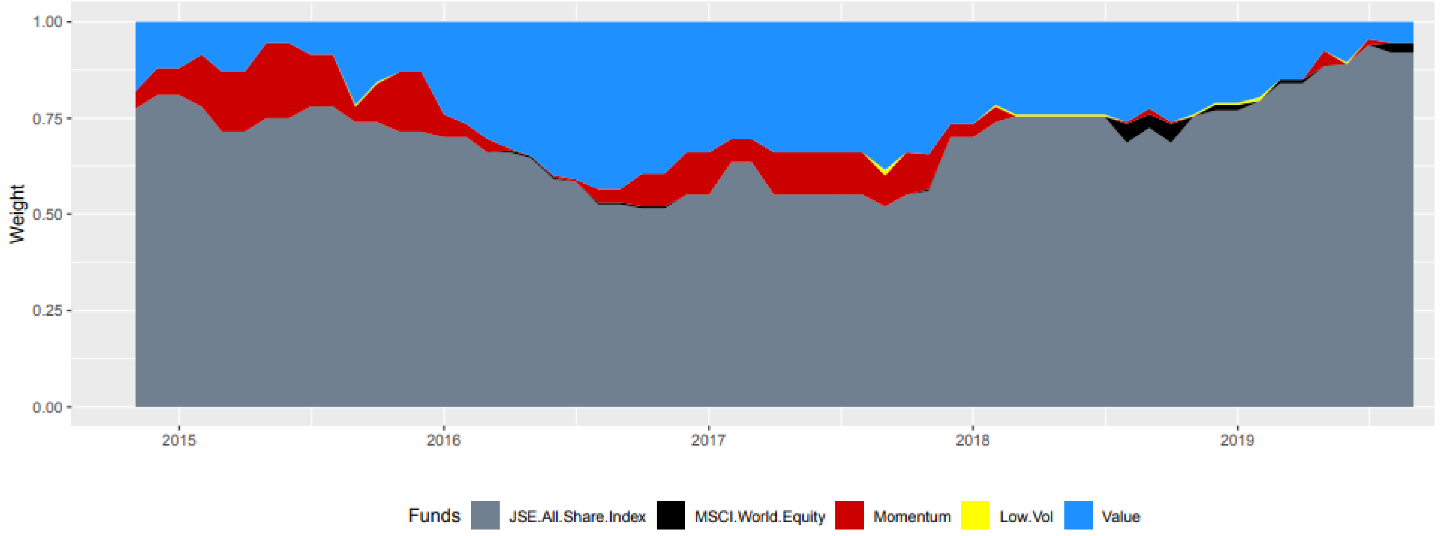
The three funds from this risk profile that were shortlisted include: (1) Coronation Balanced Defensive Fund, (2) Nedgroup Investments Stable Fund and (3) Old Mutual Real Income Fund.

Old Mutual Real Income Fund generated -1.12% alpha per annum versus its shadow fund and 0.51% alpha per annum versus its benchmark **(Table 5.6 and Figure 5.6)**. The average alpha versus shadow fund for this risk profile is -1.46% per annum, while the average alpha versus benchmark is 1.27% per annum. Old Mutual Real Income Fund has an R-squared of 0.54 and a correlation of 0.74 to its shadow fund. This indicates that the holdings of the shadow fund can explain a moderate amount of the variations of returns of Old Mutual Real Income Fund. The R-squared and correlation are significantly less than the R-squared of Coronation Balanced Defensive Fund and Nedgroup Investments Stable Fund, which is 0.82 and 0.83, respectively. Their correlation to shadow fund is 0.91 and 0.91 respectively.

What is most notable from the X-RAY and risk profile of Old Mutual Real Income Fund (**Table 5.6 and Figure 5.6)** is that 80.5% of its style is attributed to STEFI Composite Index. This is materially higher than the 61.5% STEFI Composite Index component of Coronation Balanced Defensive Fund **(Annexure K)** and the 31.5% STEFI Composite Index component of Nedgroup Investments Stable Fund **(Annexure L)**. The standard deviation of STEFI Composite Index is 0.26% per annum, making it the least risky component of the passive asset classes and style indices that form part of these funds. The significant STEFI Composite Index component of Old Mutual Real Income Fund helps reduce the total risk of the fund, and therefore, the annualised standard deviation of the fund is only 2.5%. The annualised standard deviation of Coronation Balanced Defensive Fund **(Annexure K)** and Nedgroup Investments Stable Fund **(Annexure L)** is 4.46% and 5.07% respectively.

Old Mutual Real Income Fund is selected to form part of the SA multi-asset low equity core-satellite portfolio due to the fact that the manager includes a large portion of interest baring assets to the fund which generates stable returns along with reducing the total risk of the fund. This indicates the manager can meet the needs of low-risk investors by reducing the total risk of the fund while not sacrificing returns. Finally, Old Mutual Real Income Fund has a lower R-squared and correlation to its shadow fund compared to its peers. This indicates the manager has the ability and skill to identify and include alternative asset classes to generate stable returns along with low levels of total risk, which justifies its active management fees.

Figure 5.4: Fairtree Equity Prescient Fund X-RAY Results and Cumulative Returns vs Shadow Fund



Building Blocks :

Name	Min Weight	Max Weight	Final Weight
JSE All-Share Index	0	100	92.0
Low Vol	0	100	0.0
Momentum	0	100	0.0
MSCI World Equity	0	100	2.5
Value	0	100	5.5

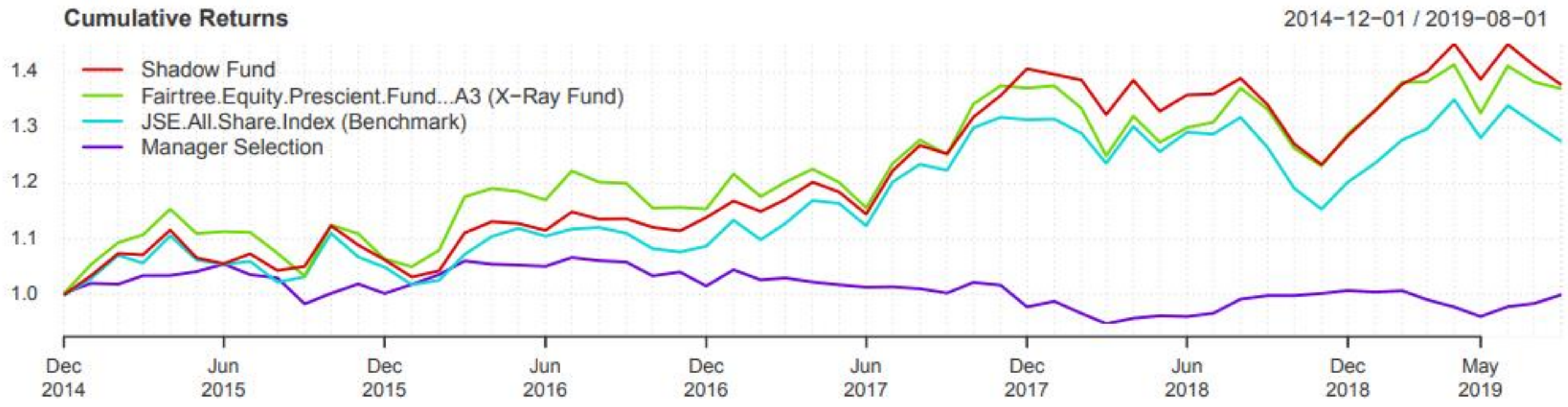
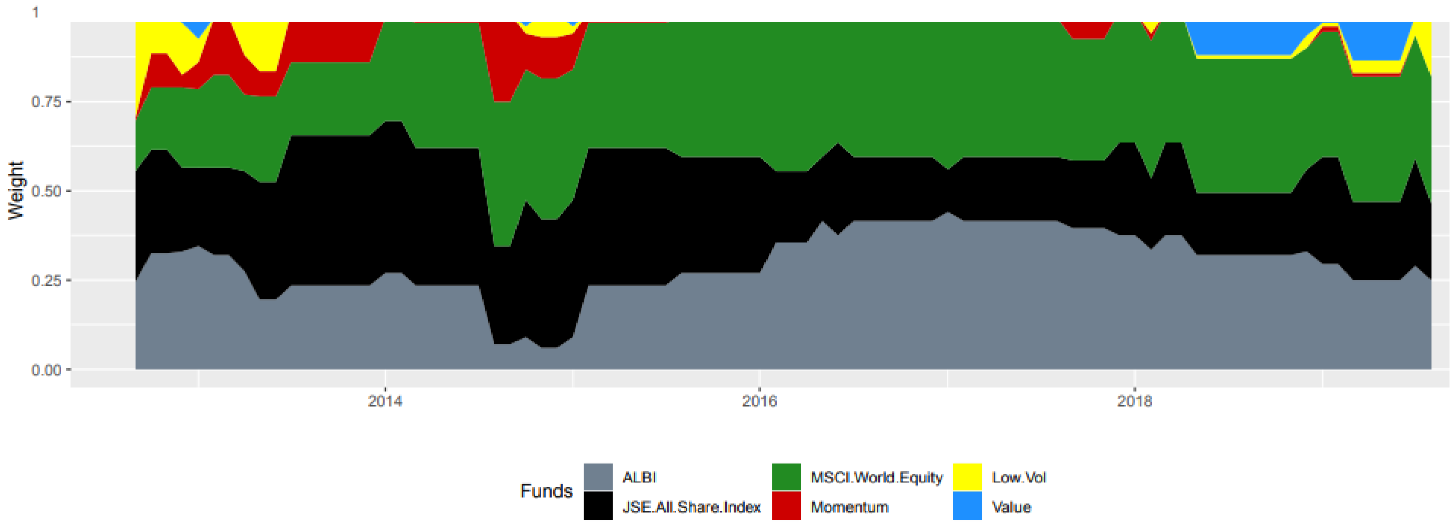


Figure 5.5: Investec Managed Fund X-RAY Results and Cumulative Returns vs Shadow Fund



Building Blocks :

Name	Min Weight	Max Weight	Final Weight
ALBI	0	100	25.0
JSE All-Share Index	0	100	21.5
Low Vol	0	100	16.0
Momentum	0	100	0.0
MSCI World Equity	0	100	35.5
Value	0	100	2.0

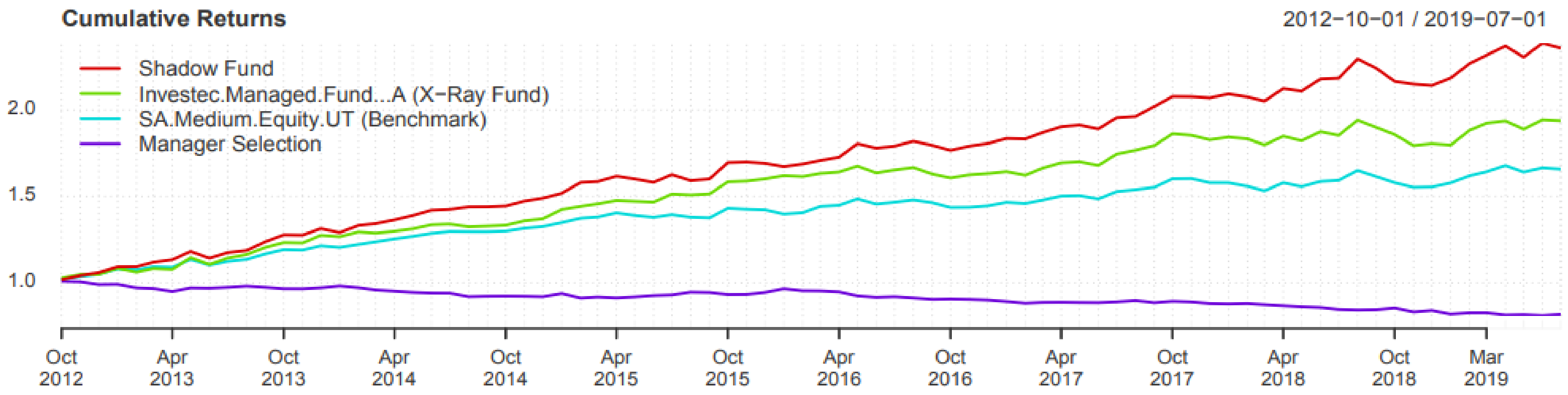
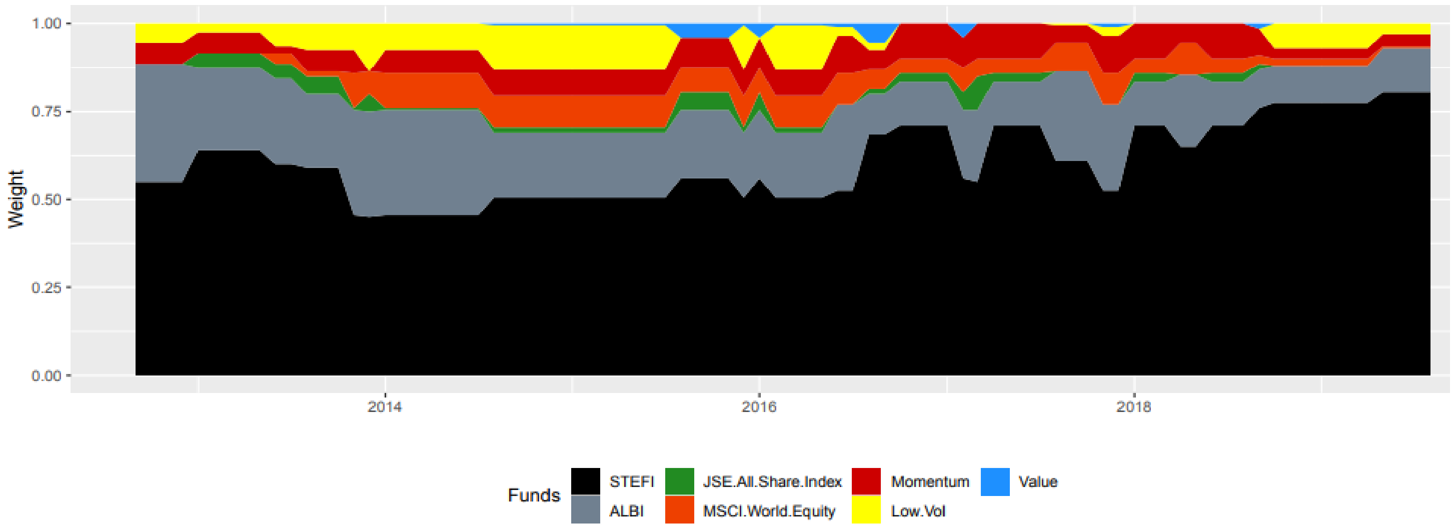
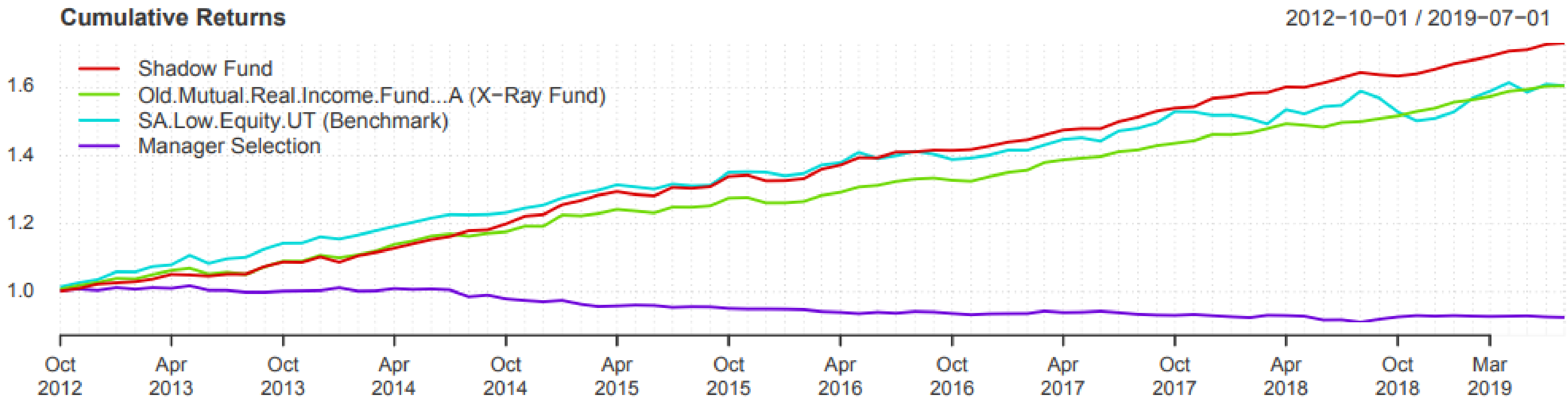


Figure 5.6: Old Mutual Real Income Fund X-RAY Results and Cumulative Returns vs Shadow Fund



Building Blocks :

Name	Min Weight	Max Weight	Final Weight
ALBI	0	100	12.5
JSE All-Share Index	0	100	0.0
Low Vol	0	100	3.0
Momentum	0	100	3.5
MSCI World Equity	0	100	0.5
STEFI	0	100	80.5
Value	0	100	0.0



5.6 Creating the Replica Portfolios – Step 3 Risk and Tracking Error Budgeting using Active, Passive and Smart Beta

The final step in creating the range of core-satellite portfolios is to use the active managers that were identified through RBSA and blending them with passive and smart-beta strategies. The analysis aims to determine the optimal blend between these strategies along with identifying whether the core component should consist of active, passive or smart-beta. The following parameters are imposed upon the portfolios:

1. **High Risk: SA General Equity**
   Maximum Tracking Error: 5.36% per annum ***(SA GE mean, Table 5.1)***
   Maximum Total Risk *"standard deviation"*: 13.06% per annum ***(Benchmark[6], Table 5.1)***
   Maximum Risk Budget *"standard deviation"* per holding: 35%
   Maximum smart-beta allocation: 15% per style factor
   Maximum equity exposure: 100%
   Maximum offshore exposure: 30%

2. **Medium Risk: SA Multi-Asset High Equity**
   Maximum Tracking Error: 5.53% per annum ***(SA MAHE mean, Table 5.2)***
   Maximum Total Risk *"standard deviation"*: 10.76% per annum ***(Benchmark[7], Table 5.2)***
   Maximum Risk Budget *"standard deviation"* per holding: 35%
   Maximum smart-beta allocation: 15% per style factor
   Maximum equity exposure: 75%
   Maximum offshore exposure: 30%

3. **Low Risk: SA Multi-Asset Low Equity**
   Maximum Tracking Error: 5.06% per annum ***(SA MALE mean, Table 5.3)***
   Maximum Total Risk *"standard deviation"*: 7.01% per annum ***(Benchmark[8], Table 5.3)***
   Maximum Risk Budget *"standard deviation"* per holding: 30%
   Maximum smart-beta allocation: 15% per style factor
   Maximum equity exposure: 40%
   Maximum offshore exposure: 30%

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[6] The maximum risk parameter for high risk portfolios may not exceed the risk of the FTSE/JSE All Share (J203T)
[7] The maximum risk parameter for medium risk portfolios may not exceed the risk of 75% FTSE/JSE + 25% ALBI
[8] The maximum risk parameter for low risk portfolios may not exceed the risk of 40% FTSE/JSE + 40% ALBI + 20% STeFI

Table 5.7: Core-Satellite SA General Equity Portfolio Results

	High Risk: SA General Equity (Dec 2011 – Sep 2019)			
FUND	**Total Return (% p.a.)**	**Total Risk (% p.a.)**	**Tracking Error (% p.a.)**	**Sharpe Ratio**
Fairtree Equity Prescient Fund	12.84	11.98	4.88	0.53
Stanlib ALSI 40 Fund	8.95	12.26	2.67	0.22
Sygnia Itrix MSCI World Index ETF	16.99	14.76	14.42	0.73
A-DEX SA Momentum Fund	13.86	11.4	8.69	0.67
A-DEX SA Low Volatility Fund	12.05	9.3	8.57	0.62
A-DEX SA Value Fund	16.02	11.92	9.45	0.82

	Within Parameters[9]		*Outside Parameters (TE < 6%)*[10]		*Outside Parameters (TE < 7%)*[11]	
PORTFOLIO HOLDINGS	**Allocation (%)**	**Risk Contribution (%)**	**Allocation (%)**	**Risk Contribution (%)**	**Allocation (%)**	**Risk Contribution (%)**
Fairtree Equity Prescient Fund	15.00	15.68	0.00	0.00	0.00	0.00
Stanlib ALSI 40 Fund	30.00	31.93	10.00	10.37	0.00	0.00
Sygnia Itrix MSCI World Index ETF	30.00	33.55	26.00	18.30	30.00	20.70
A-DEX SA Momentum Fund	10.00	7.02	6.00	5.97	2.00	1.95
A-DEX SA Low Volatility Fund	5.00	8.52	0.00	0.00	2.00	1.58
A-DEX SA Value Fund	10.00	3.30	58.00	65.36	66.00	75.77
Portfolio Total Return (% p.a.)	**13.73**		**15.97**		**16.66**	
Portfolio Total Risk (% p.a.)	**9.90**		**9.41**		**9.36**	
Portfolio Tracking Error (% p.a.)	**4.65**		**5.97**		**6.73**	
Portfolio Sharpe Ratio	**0.76**		**1.03**		**1.11**	

[9] Refers to the asset allocation, smart-beta allocation, geographical allocation, total risk, risk contribution per holding and tracking error parameters imposed on the core-satellite portfolio.
[10] Asset allocation and geographical allocation parameters still imply. However, smart-beta limitations, risk contribution per holding and tracking error parameters no longer apply.
[11] Asset allocation and geographical allocation parameters still imply. However, smart-beta limitations, risk contribution per holding and tracking error parameters no longer apply.

Figure 5.7: SA General Equity Feasible Set of Portfolios

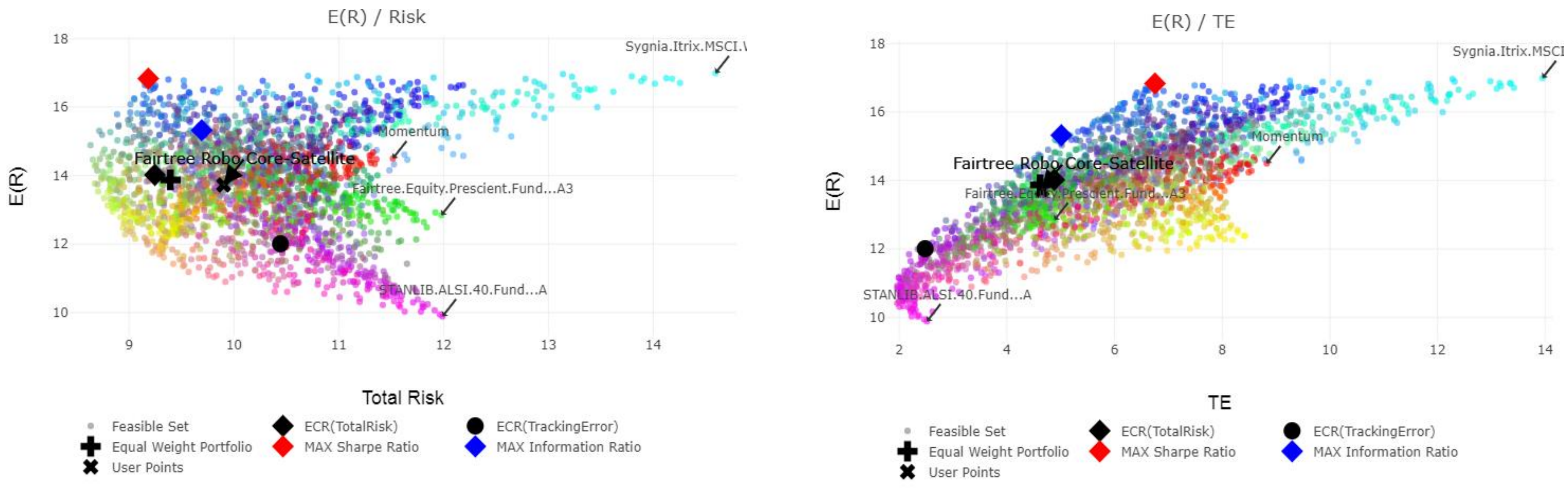


Table 5.8: Fairtree Robo Core-Satellite Portfolio vs Benchmark

	Trailing Results[12]	
	Fairtree Robo Core-Satellite Portfolio[13]	**Benchmark FTSE/JSE All Share (J203T)**
Last 12 Month Ann Returns	4.78%	1.08%
Last 24 Month Ann Returns	5.81%	2.19%
Last 36 Month Ann Returns	6.88%	4.80%
Last 60 Month Ann Returns	8.31%	5.35%

[12] Fairtree Robo Core-Satellite Portfolio vs Benchmark (FTSE/JSE All Share (J203T)) performance chart can be seen on **Figure 5.8**.
[13] Fairtree Robo Core-Satellite Portfolio can be seen on its theoretical efficient frontier **(Figure 5.7)** indicating its risk and return and risk and tracking error trade off.

Figure 5.8: Fairtree Robo Core-Satellite Portfolio vs Benchmark (FTSE/JSE All Share (J203T)) Cumulative Performance

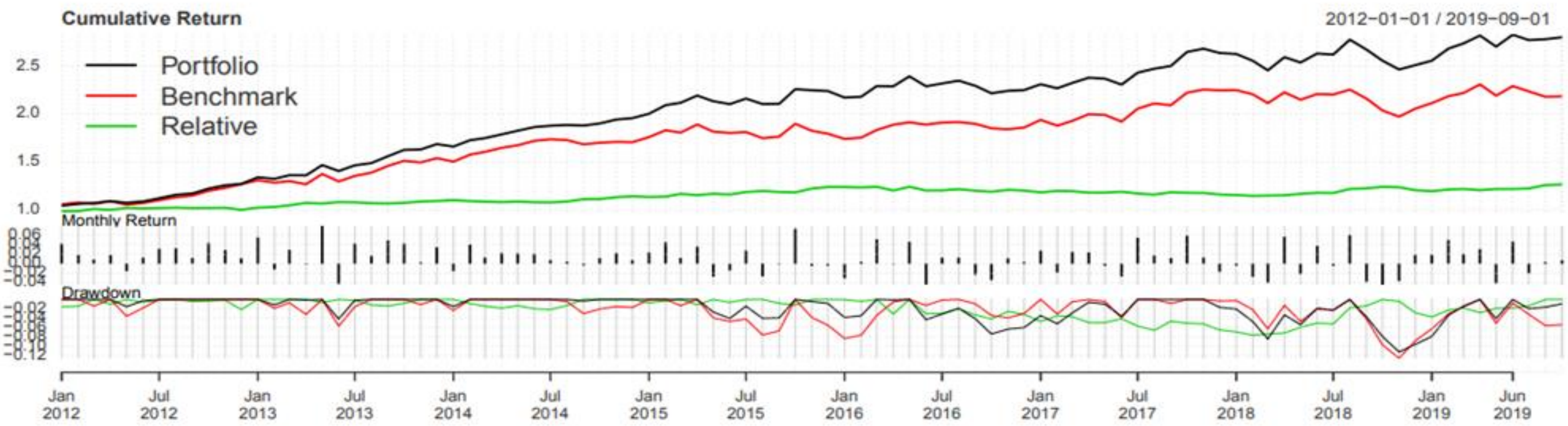
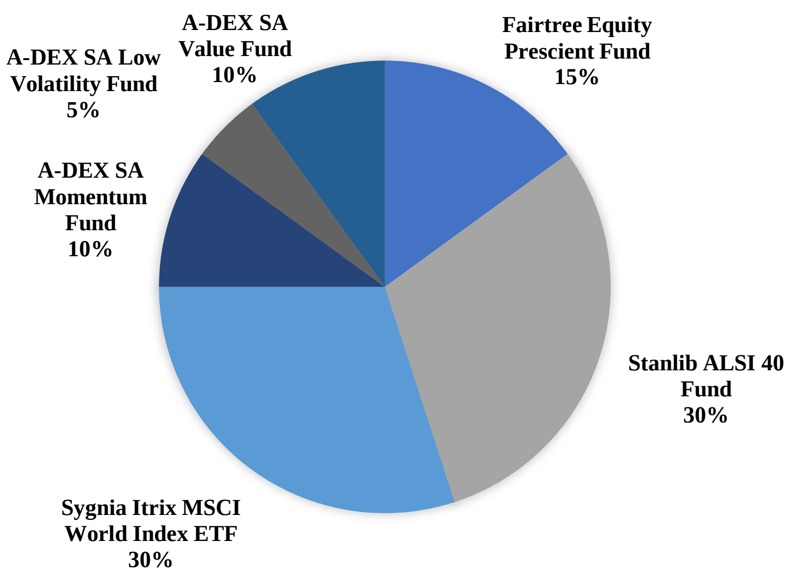


Figure 5.9: Fairtree Robo Core-Satellite Portfolio Holdings and Asset Allocation



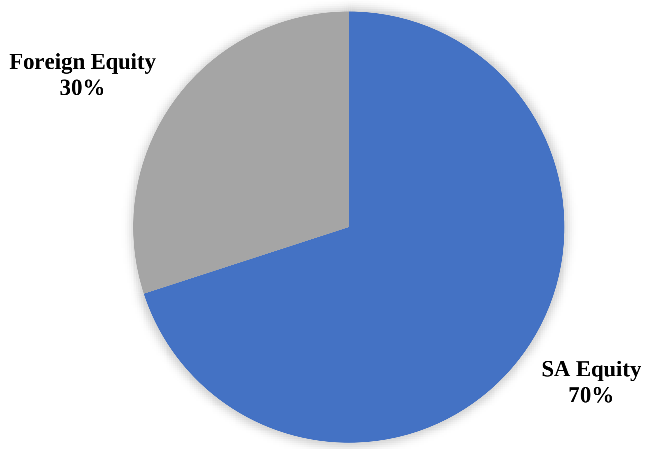


Table 5.9: Core-Satellite SA Multi-Asset High Equity Portfolio Results

	Medium Risk: SA Multi-Asset High Equity Building Blocks (Oct 2009 – Sep 2019)					
FUND	**Total Return (% p.a.)**	**Total Risk (% p.a.)**	**Tracking Error (% p.a.)**	**Sharpe Ratio**		
Investec Managed Fund	11.31	7.07	6.07	0.68		
Stanlib ALSI 40 Fund	10.62	12.82	4.95	0.32		
Sygnia Itrix MSCI World Index ETF	14.59	14.31	14.5	0.56		
A-DEX SA Momentum Fund	16.77	12.01	7.98	0.85		
A-DEX SA Low Volatility Fund	15.19	9.63	7.54	0.9		
A-DEX SA Value Fund	18.51	13.43	8.05	0.89		
Nedgroup Investments Core Income Fund	7.04	0.42	9.23	1.26		
	Within Parameters[14]		*Outside Parameters (TE < 6%)*[15]		*Outside Parameters (TE < 7%)*[16]	
PORTFOLIO HOLDINGS	**Allocation (%)**	**Risk Contribution (%)**	**Allocation (%)**	**Risk Contribution (%)**	**Allocation (%)**	**Risk Contribution (%)**
Investec Managed Fund	41.00	34.08	10.00	8.52	0.00	0.00
Stanlib ALSI 40 Fund	16.00	21.40	5.00	7.53	0.00	0.00
Sygnia Itrix MSCI World Index ETF	17.00	22.94	27.00	37.69	30.00	42.27
A-DEX SA Momentum Fund	6.00	10.08	5.00	34.25	9.00	39.89
A-DEX SA Low Volatility Fund	6.00	6.59	6.00	6.31	6.00	11.93
A-DEX SA Value Fund	10.00	4.90	27.00	5.74	30.00	6.00
Nedgroup Investments Core Income Fund	4.00	0.00	20.00	0.00	25.00	0.00
Portfolio Total Return (% p.a.)	**12.46**		**13.10**		**13.35**	
Portfolio Total Risk (% p.a.)	**8.00**		**7.16**		**6.98**	
Portfolio Tracking Error (% p.a.)	**4.91**		**5.43**		**5.79**	
Portfolio Sharpe Ratio	**0.75**		**0.92**		**0.99**	

[14] Refers to the asset allocation, smart-beta allocation, geographical allocation, total risk, risk contribution per holding and tracking error parameters imposed on the core-satellite portfolio.
[15] Asset allocation and geographical allocation parameters still imply. However, smart-beta limitations, risk contribution per holding and tracking error parameters no longer apply.
[16] Asset allocation and geographical allocation parameters still imply. However, smart-beta limitations, risk contribution per holding and tracking error parameters no longer apply.

Figure 5.10: SA Multi-Asset High Equity Feasible Set of Portfolios

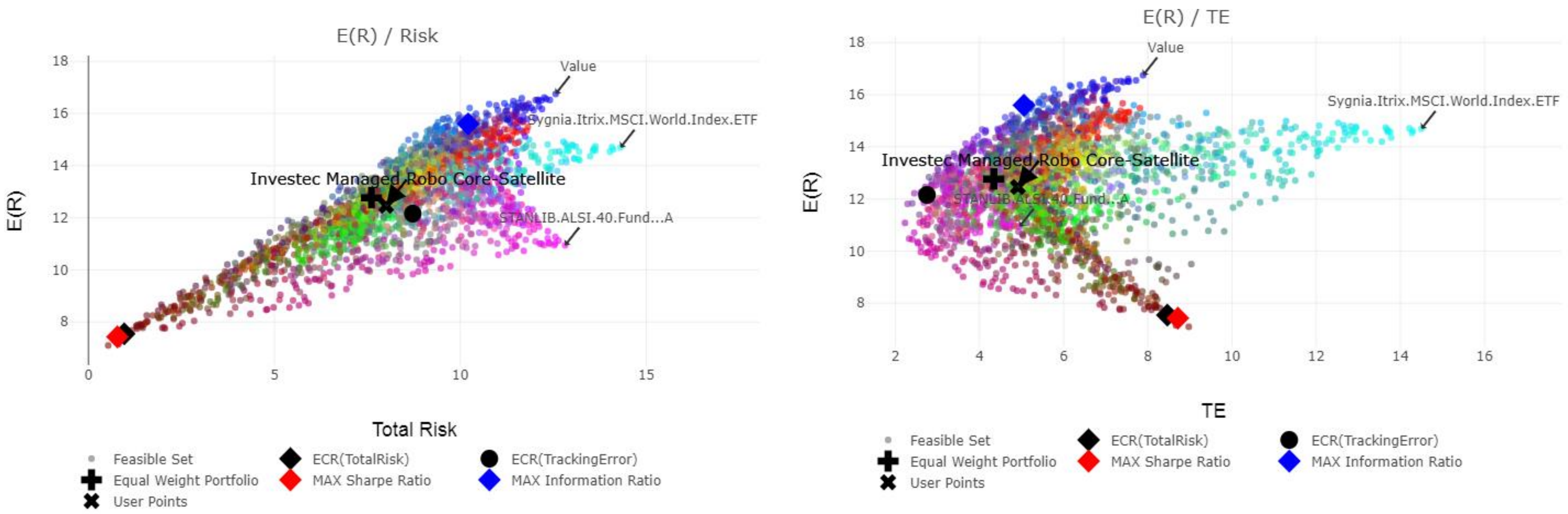


Table 5.10: Investec Managed Core-Satellite Portfolio vs Benchmark

	Trailing Results[17]	
	Investec Managed Robo Core-Satellite[18]	**Benchmark 75% FTSE/JSE + 25% ALBI**
Last 12 Month Ann Returns	5.47%	8.83%
Last 24 Month Ann Returns	5.55%	7.64%
Last 36 Month Ann Returns	6.70%	8.02%
Last 60 Month Ann Returns	8.27%	7.94%

[17] Investec Managed Core-Satellite Portfolio vs Benchmark (75% FTSE/JSE + 25% ALBI) performance chart can be seen on **Figure 5.11.**
[18] Investec Managed Core-Satellite Portfolio can be seen on its theoretical efficient frontier **(Figure 5.10)** indicating its risk and return and risk and tracking error trade off.

Figure 5.11: Investec Managed Core-Satellite Portfolio vs Benchmark (75% FTSE/JSE + 25% ALBI) Cumulative Performance

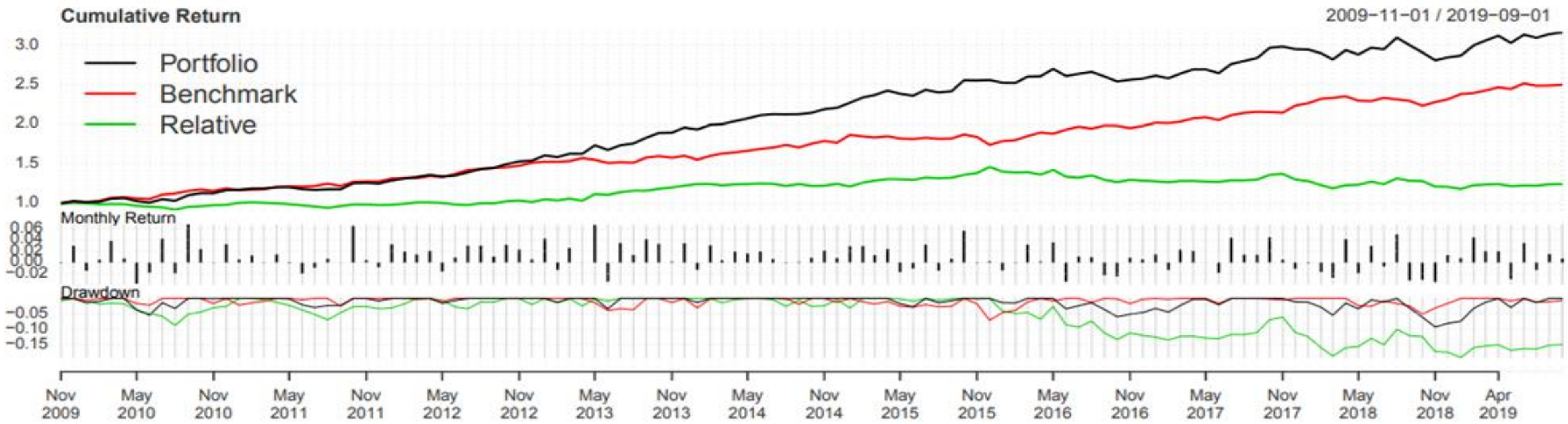
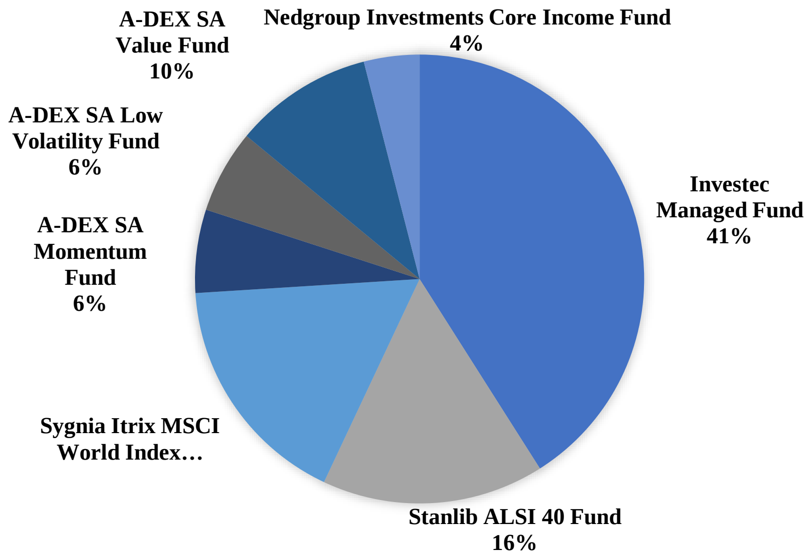


Figure 5.12: Investec Managed Robo Core-Satellite Portfolio Holdings and Asset Allocation



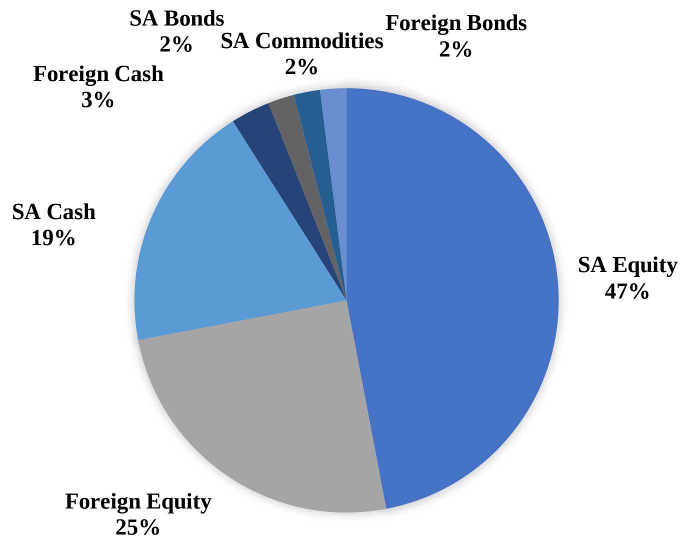


Table 5.11: Core-Satellite SA Multi-Asset Low Equity Portfolio Results

Low Risk: SA Multi-Asset Low Equity Building Blocks (Oct 2009 – Sep 2019)						
FUND	**Total Return (% p.a.)**	**Total Risk (% p.a.)**	**Tracking Error (% p.a.)**	**Sharpe Ratio**		
Old Mutual Real Income Fund	8.48	2.54	4.38	0.78		
Stanlib ALSI 40 Fund	10.62	12.82	4.95	0.32		
Sygnia Itrix MSCI World Index ETF	14.59	14.31	14.5	0.56		
A-DEX SA Momentum Fund	16.77	12.01	7.98	0.85		
A-DEX SA Low Volatility Fund	15.19	9.63	7.54	0.9		
A-DEX SA Value Fund	18.51	13.43	8.05	0.89		
Nedgroup Investments Core Income Fund	7.04	0.42	9.23	1.26		
	Within Parameters[19]		*Outside Parameters (TE < 4.1%)*[20]		*Outside Parameters (TE < 4.5%)*[21]	
PORTFOLIO HOLDINGS	**Allocation (%)**	**Risk Contribution (%)**	**Allocation (%)**	**Risk Contribution (%)**	**Allocation (%)**	**Risk Contribution (%)**
Old Mutual Real Income Fund	45.00	22.51	20.00	8.02	10.00	3.55
Stanlib ALSI 40 Fund	4.00	11.96	2.00	5.78	0.00	0.00
Sygnia Itrix MSCI World Index ETF	12.00	29.09	15.00	38.24	17.00	45.36
A-DEX SA Momentum Fund	2.00	22.84	2.00	41.03	2.00	44.53
A-DEX SA Low Volatility Fund	4.00	5.34	1.00	4.98	1.00	4.75
A-DEX SA Value Fund	9.00	8.19	16.00	1.88	18.00	1.80
Nedgroup Investments Core Income Fund	24.00	0.00	44.00	0.00	52.00	0.02
Portfolio Total Return (% p.a.)	**9.89**		**10.19**		**10.33**	
Portfolio Total Risk (% p.a.)	**3.61**		**3.70**		**3.73**	
Portfolio Tracking Error (% p.a.)	**3.80**		**4.02**		**4.27**	
Portfolio Sharpe Ratio	**0.93**		**0.98**		**0.98**	

[19] Refers to the asset allocation, smart-beta allocation, geographical allocation, total risk, risk contribution per holding and tracking error parameters imposed on the core-satellite portfolio.
[20] Asset allocation and geographical allocation parameters still imply. However, smart-beta limitations, risk contribution per holding and tracking error parameters no longer apply.
[21] Asset allocation and geographical allocation parameters still imply. However, smart-beta limitations, risk contribution per holding and tracking error parameters no longer apply.

Figure 5.13: SA Multi-Asset Low Equity Feasible Set of Portfolios

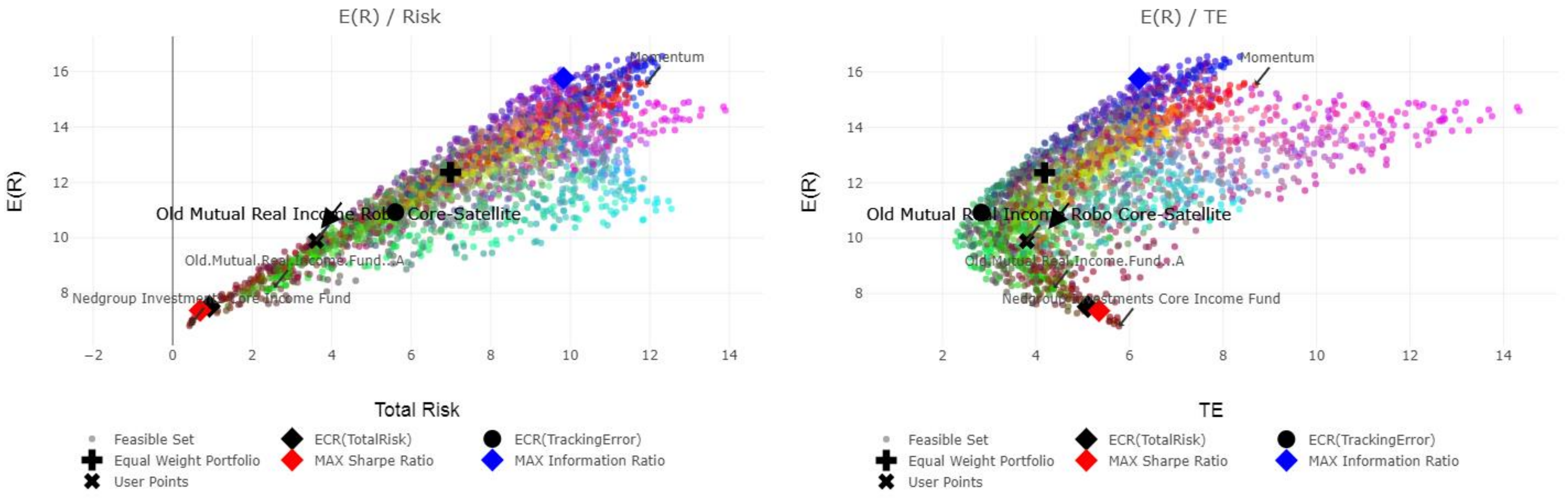


Table 5.12: Old Mutual Real Income Core-Satellite Portfolio vs Benchmark

	Trailing Results[22]	
	Old Mutual Real Income Robo Core-Satellite[23]	**Benchmark 40% FTSE/JSE + 40% ALBI + 20% STeFI**
Last 12 Month Ann Returns	7.03%	7.76%
Last 24 Month Ann Returns	6.54%	7.21%
Last 36 Month Ann Returns	6.83%	7.63%
Last 60 Month Ann Returns	7.58%	7.51%

[22] Old Mutual Real Income Core-Satellite Portfolio vs Benchmark (40% FTSE/JSE + 40% ALBI + 20% STeFI) performance chart can be seen on **Figure 5.14**.

[23] Old Mutual Real Income Core-Satellite Portfolio can be seen on its theoretical efficient frontier **(Figure 5.13)** indicating its risk and return and risk and tracking error trade off.

Figure 5.15: Old Mutual Real Income Core-Satellite Portfolio vs Benchmark (40% FTSE/JSE + 40% ALBI + 20% STeFI) Cumulative Performance

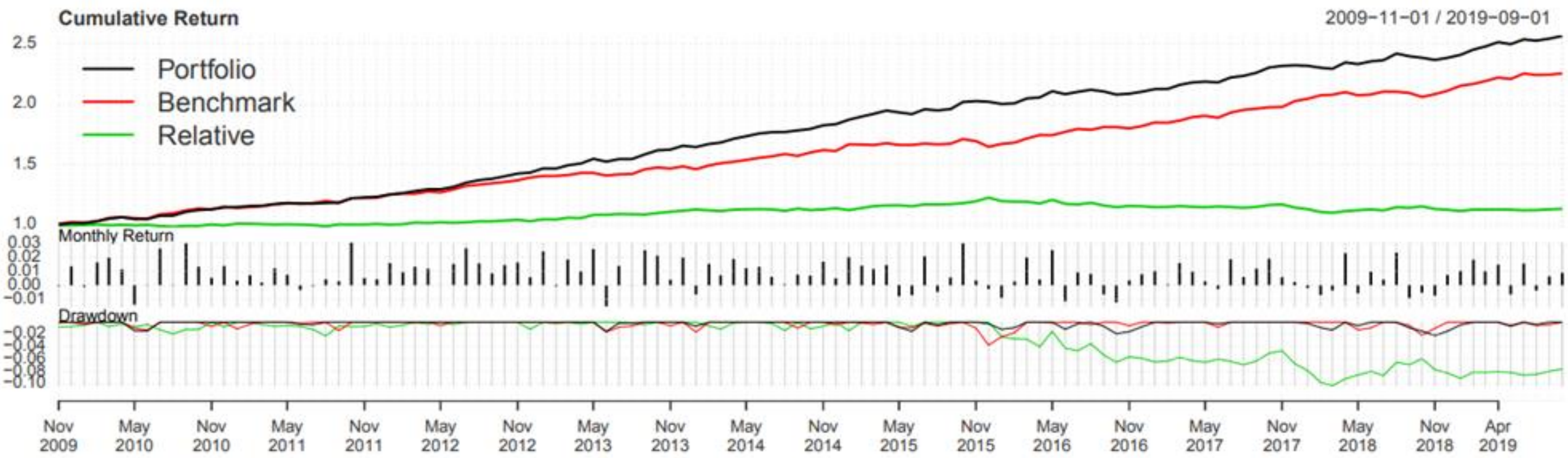
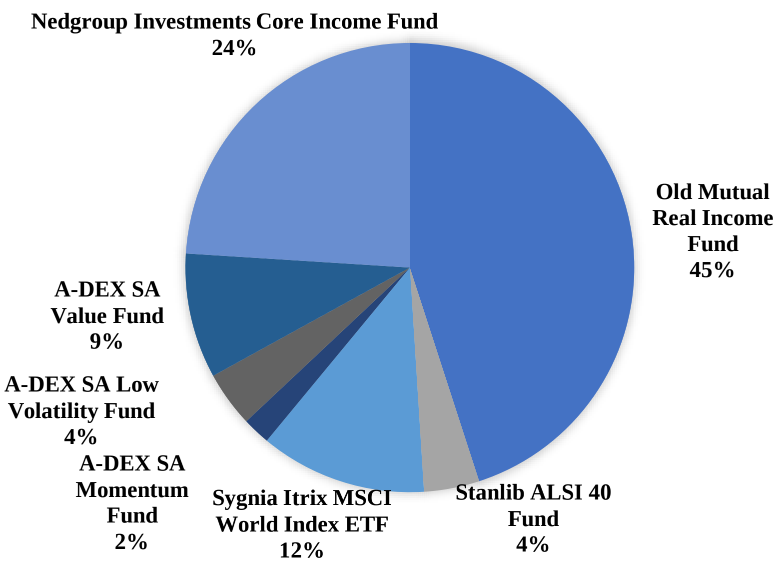
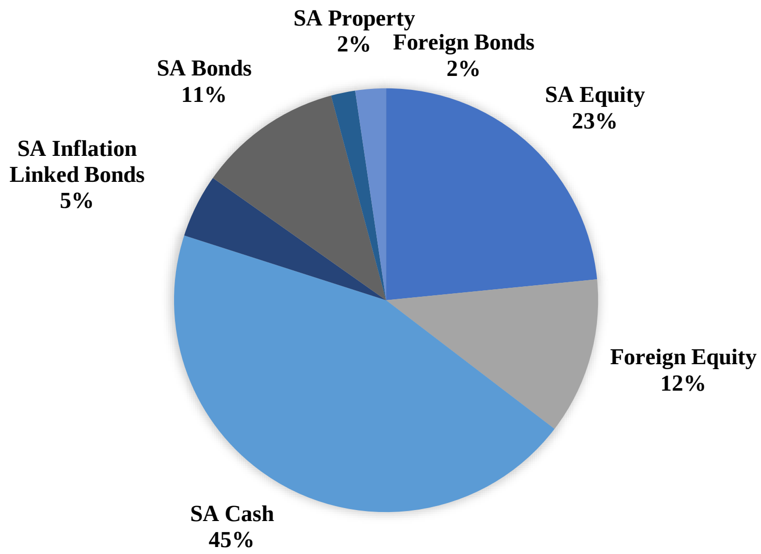


Figure 5.14: Old Mutual Real Income Robo Core-Satellite Portfolio Holdings and Asset Allocation





5.7 Results and Conclusion – Risk and Tracking Error Budgeting using Active, Passive and Smart Beta

The analysis seeks to develop a product range of low-cost core-satellite portfolios for the following risk profiles:

1. High Risk: SA General Equity
2. Medium Risk: SA Multi-Asset High Equity
3. Low Risk: SA Multi-Asset Low Equity

The range of core-satellite portfolios that were developed have several restrictions and limitations[24] imposed on them in order to comply with ASISA's framework. The results and conclusion from each *"replica portfolio"* will be discussed in this section in order to determine whether these portfolios have achieved their desired outcome.

5.7.1 Conclusion - High Risk: SA General Equity Core-Satellite Product

The product that was developed is called **Fairtree Robo Core-Satellite Portfolio (Table 5.7)**. The primary considerations in developing the portfolio were total risk, tracking error, risk contribution per holding along with low total fees as measured by the TIC of the portfolio. The secondary objective aimed at optimising the risk-adjusted returns of the portfolio. The portfolio was developed in line with the SAA bounds and restrictions set out by ASISA for SA General Equity Portfolios[25].

Applying Euler's theorem for homogenous functions along with tracking error and total risk budgeting, the **Fairtree Robo Core-Satellite Portfolio** was developed. The portfolio consists of six holdings in total **(Figure 5.9)**, of which one is active, two are passive along with three smart-beta components. Fairtree Equity Prescient Fund actively manages 15% of the portfolio. 60% consists of pure passive, of which 30% is allocated to Stanlib ALSI 40 Fund and 30% to Sygnia Itrix MSCI World Index ETF. Finally, 25% is allocated to A-DEX smart-beta funds. The composition of the portfolio indicates that the core consists of passive and smart-beta, low-cost holdings while the satellite of the portfolio consists of one active manager.

[24] Refers to the asset allocation, smart-beta allocation, geographical allocation, total risk, risk contribution per holding and tracking error parameters imposed on the core-satellite portfolio.
[25] SA General Equity funds must invest a minimum of 80% of the market value of the portfolios in equities. 30% of their assets may be invested outside South Africa.

Fairtree Robo Core-Satellite Portfolio generated a net annualised return of **13.73%** over the period 1 Dec 2011 to 30 Sep 2019. This is significantly higher than the return of the benchmark FTSE/JSE All Share (J203T) of 9.66% p.a. as well as the net return of Fairtree Equity Prescient Fund of 12.84% p.a. The total risk of the portfolio over the sample period was **9.90% p.a.**, which is less than its benchmark of 11.05% p.a. The most substantial risk contribution per holding is 33.55%, which stems from Sygnia Itrix MSCI World Index ETF, indicating that global equity is the most significant contributor to risk. The tracking error vs benchmark of the portfolio was **4.65%** p.a., which is lower than the mean tracking error of SA General Equity funds included in the sample of 5.36% p.a. The Sharpe Ratio of the portfolio over the sample period was **0.76**, which is higher than the average Sharpe Ratio of 0.26 for SA General Equity funds included in the study. Applying a fee analysis, **Fairtree Robo Core-Satellite Portfolio** has a TIC of **0.80%** p.a. **(Table 5.13).** The weighted TIC of the portfolio is significantly less than the TIC of comparable actively managed SA General Equity Funds[26].

Table 5.13: Fee Analysis: Fairtree Robo Core-Satellite Portfolio

Fee Analysis: SA General Equity Building Blocks			
PORTFOLIO HOLDINGS	**Allocation (%)**	**TIC (%)**	**Weighted TIC (%)**
Fairtree Equity Prescient Fund	15.00%	2.71%	0.41%
Stanlib ALSI 40 Fund	30.00%	0.52%	0.16%
Sygnia Itrix MSCI World Index ETF	30.00%	0.68%	0.20%
A-DEX SA Momentum Fund	10.00%	0.15%	0.02%
A-DEX SA Low Volatility Fund	5.00%	0.15%	0.01%
A-DEX SA Value Fund	10.00%	0.15%	0.02%
Fairtree Robo Core-Satellite TIC (%)			**0.80%**

Finally, the analysis develops additional core-satellite portfolios that do not comply with the parameters[27]. The composition of the portfolios are similar to the findings of Waring *et al.* (2000), in that tracking error and active risk increases as the allocation towards non-passive managers increase. The tracking error vs benchmark of these portfolios increase as their allocation towards smart-beta funds increases. However, the portfolios generate higher absolute returns with lower total risk. Thus, increasing the Sharpe Ratio of the portfolio. This phenomenon can be attributed to the cutting-edge quantitative portfolio characteristics of A-DEX smart-beta funds which support the findings of Arnott, Hsu and Moore (2005).

[26] The average TIC of active SA General Equity Funds shortlisted in this analysis is 2.37% p.a.
[27] Asset allocation and geographical allocation parameters still imply. However, smart-beta limitations, risk contribution per holding and tracking error parameters no longer apply.

5.7.2 Conclusion - Medium Risk: SA Multi-Asset High Equity Core-Satellite Product

The product that was developed is called **Investec Managed Robo Core-Satellite Portfolio (Table 5.9)**. The primary considerations in developing the portfolio was total risk, tracking error, risk contribution per holding along with low total fees as measured by the TIC of the portfolio. The secondary objective aimed at optimising the risk-adjusted returns of the portfolio. The portfolio was developed in line with the SAA bounds and restrictions set out by ASISA for SA Multi-Asset High Equity Portfolios[28].

Applying Euler's theorem for homogenous functions along with tracking error and total risk budgeting, the **Investec Managed Robo Core-Satellite Portfolio** was developed. The portfolio consists of seven holdings in total **(Figure 5.12)**, of which two are active, two are passive along with three smart-beta components. 45% of the portfolios consist of pure active, 41% of which is managed by Investec Managed Fund. 4% of the portfolio is managed by Nedgroup Investments Core Income Fund, which seeks to replicate the performance of the STeFI Composite index, at a low-cost. 33% consists of pure passive, of which 16% is allocated to Stanlib ALSI 40 Fund and 17% to Sygnia Itrix MSCI World Index ETF. Finally, 22% is allocated to A-DEX smart-beta funds. The composition of the portfolio is unlike the Fairtree Robo Core-Satellite Portfolio since the core component, in this case, is allocated to active managers. The satellite component of the portfolio consists of passive and smart-beta holdings. These findings suggest that the inclusion of active managers within the context of multi-asset portfolios should be a key consideration for advisors. Particularly if the manager can generate positive risk-adjusted returns with a low R-squared. The R-squared of Investec Managed fund to its passive asset classes and style indices is 0.73, which is less than its peers[29].

Investec Managed Robo Core-Satellite Portfolio generated a net annualised return of **12.46%** over the period 1 Oct 2009 to 30 Sep 2019. This is higher than the return of the benchmark (75% FTSE/JSE + 25% ALBI) of 11.49% p.a. as well as the net return of Investec Managed Fund of 11.30% p.a. The total risk of the portfolio over the sample period was **8.00%** p.a., which is less than its benchmark of 10.76% p.a. The most substantial risk contribution per holding is 34.08%, which stems from Investec Managed Fund. This indicates that active risk

[28] SA Multi-Asset High Equity Funds may invest in up to 75% equities. 30% of their assets may be invested outside South Africa.

[29] The R-squared of Prudential Balanced Fund and Stanlib Multi-Manager Balanced Fund is 0.90 and 0.88 respectively.

forms the largest contribution to total risk. The tracking error vs benchmark of the portfolio was **4.91%** p.a., which is lower than the mean tracking error of SA Multi-Asset High Equity funds included in the sample of 5.53% p.a. The Sharpe Ratio of the portfolio over the sample period was **0.75**, which is higher than the average Sharpe Ratio of 0.43 for SA Multi-Asset High Equity funds included in the study. Applying a fee analysis, **Investec Managed Robo Core-Satellite Portfolio** has a TIC of **1.11%** p.a. **(Table 5.14).** The weighted TIC of the portfolio is significantly less than the TIC of comparable actively managed SA Multi-Asset High Equity Funds [30].

Table 5.14: Fee Analysis: Investec Managed Robo Core-Satellite Portfolio

Fee Analysis: SA Multi-Asset High Equity Building Blocks			
PORTFOLIO HOLDINGS	**Allocation (%)**	**TIC (%)**	**Weighted TIC (%)**
Investec Managed Fund	41.00%	2.08%	0.85%
Stanlib ALSI 40 Fund	16.00%	0.52%	0.08%
Sygnia Itrix MSCI World Index ETF	17.00%	0.68%	0.12%
A-DEX SA Momentum Fund	6.00%	0.15%	0.01%
A-DEX SA Low Volatility Fund	6.00%	0.15%	0.01%
A-DEX SA Value Fund	10.00%	0.15%	0.02%
Nedgroup Investments Core Income Fund	4.00%	0.59%	0.02%
Investec Managed Robo Core-Satellite TIC (%)			**1.11%**

Finally, the analysis develops additional core-satellite portfolios that do not comply with the parameters[31]. The composition of the portfolios are similar to the findings of Waring *et al*. (2000), in that tracking error and active risk increases as the allocation towards non-passive managers increase. The tracking error vs benchmark of these portfolios increase as their allocation towards smart-beta funds increases, however the portfolios generate higher absolute returns with lower total risk. Thus, again increasing the Sharpe Ratio of the portfolio as in the case of SA General Equity portfolios. Once again, this points out the cutting-edge quantitative portfolio characteristics of A-DEX smart-beta funds which support the findings of Arnott, Hsu and Moore (2005). Unfortunately, SA Multi-Asset High Equity portfolios may not exceed a 75% allocation towards equities. Therefore, blending a global equity ETF, SA cash product and A-DEX smart-beta funds generate the optimal Sharpe Ratio. This blend does, however, have a much higher tracking error versus **Investec Managed Robo Core-Satellite Portfolio.**

[30] The average TIC of active SA Multi-Asset High Equity Funds shortlisted in this analysis is 1.75% p.a.
[31] Asset allocation and geographical allocation parameters still imply. However, smart-beta limitations, risk contribution per holding and tracking error parameters no longer apply.

5.7.3 Conclusion - Low Risk: SA Multi-Asset Low Equity Core-Satellite Product

The product that was developed is called **Old Mutual Real Income Robo Core-Satellite Portfolio (Table 5.11)**. The primary considerations in developing the portfolio was total risk, tracking error, risk contribution per holding along with low total fees as measured by the TIC of the portfolio. The secondary objective aimed at optimising the risk-adjusted returns of the portfolio. The portfolio was developed in line with the SAA bounds and restrictions set out by ASISA for SA Multi-Asset Low Equity Portfolios[32].

Applying Euler's theorem along with tracking error and total risk budgeting, the **Old Mutual Real Income Robo Core-Satellite Portfolio** was developed. The portfolio consists of seven holdings in total **(Figure 5.15)**, of which two are active, two are passive along with three smart-beta components. 69% of the portfolios consist of pure active, 45% of which is managed by Old Mutual Real Income fund. 24% of the portfolio is managed by Nedgroup Investments Core Income Fund, which seeks to replicate the performance of the STeFI Composite index, at a low-cost. 16% consists of pure passive, of which 4% is allocated to Stanlib ALSI 40 Fund and 12% to Sygnia Itrix MSCI World Index ETF. Finally, 15% is allocated to A-DEX smart-beta funds. The analysis points out that the composition of the portfolio is unlike the Fairtree Robo Core-Satellite Portfolio or Investec Managed Robo Core-Satellite Portfolio, since active managers dominate the core component in this case. The satellite component of the portfolio consists of passive and smart-beta holdings. This indicates the inclusion of active managers within the context of multi-asset low equity portfolios should be a key consideration for advisors, more so than with equity only, or multi-asset high equity portfolios. Particularly if the manager has the ability to generate positive risk-adjusted returns with a low R-squared. The R-squared of Old Mutual Real Income fund to its passive asset classes and style indices is 0.54, which is less than its peers[33].

Old Mutual Real Income Robo Core-Satellite Portfolio generated a net return of **9.89% p.a.** over the period 1 Oct 2009 to 30 Sep 2019. This is higher than the return of the benchmark (40% FTSE/JSE + 40% ALBI + 20% STeFI) of 9.80% p.a. as well as the net return of Old Mutual Real Income fund of 8.48% p.a. The total risk of the portfolio over the sample period

[32] SA Multi-Asset Low Equity Funds may invest in up to 40% equites. 30% of their assets may be invested outside South Africa.

[33] The R-squared of Coronation Balanced Defensive Fund and Nedgroup Investments Stable Fund which is 0.82 and 0.83 respectively.

was **3.61%** p.a., which is less than its benchmark of 7.01% p.a. The most substantial risk contribution per holding is 29.09%, which stems from Sygnia Itrix MSCI World Index ETF. Sygnia Itrix MSCI World Index ETF is the third-largest constituent of the portfolio. However, it is the largest contributor to total risk. The tracking error vs benchmark of the portfolio was **3.80%** p.a., which is lower than the mean tracking error of SA Multi-Asset Low Equity funds included in the sample of 5.06% p.a. The Sharpe Ratio of the portfolio over the sample period was **0.93**, which is higher than the average Sharpe Ratio of 0.51 for SA Multi-Asset Low Equity funds included in the study. Applying a fee analysis, **Old Mutual Real Income Robo Core-Satellite Portfolio** has a TIC of **0.92% (Table 5.15).** The weighted TIC of the portfolio is significantly less than the TIC of comparable actively managed SA Multi-Asset Low Equity Funds [34].

Table 5.15: Fee Analysis: Old Mutual Real Income Robo Core-Satellite Portfolio

Fee Analysis: SA Multi-Asset Low Equity Building Blocks			
PORTFOLIO HOLDINGS	**Allocation (%)**	**TIC (%)**	**Weighted TIC (%)**
Old Mutual Real Income Fund	45.00%	1.45%	0.65%
Stanlib ALSI 40 Fund	4.00%	0.52%	0.02%
Sygnia Itrix MSCI World Index ETF	12.00%	0.68%	0.08%
A-DEX SA Momentum Fund	2.00%	0.15%	0.00%
A-DEX SA Low Volatility Fund	4.00%	0.15%	0.01%
A-DEX SA Value Fund	9.00%	0.15%	0.01%
Nedgroup Investments Core Income Fund	24.00%	0.59%	0.14%
Old Mutual Real Income Robo Core-Satellite TIC (%)			**0.92%**

Finally, the analysis develops additional core-satellite portfolios that do not comply with the parameters[35]. The tracking error vs benchmark and total risk of these portfolios increase as their allocation towards smart-beta funds and global equities increase. This increases absolute returns that are significant enough to increase the Sharpe Ratios of the portfolios. SA Multi-Asset Low Equity portfolios may only invest up to 40% in equities. Therefore, the impact of larger equity and global equity allocations are significant when it comes to the total risk and tracking error of the portfolio. One of the main shortcomings of global equity allocations within low-risk portfolios is their significant contribution to risk. Limiting the extent to which low risk portfolios are exposed to global equities should be a primary consideration to advisors.

[34] The average TIC of active SA Multi-Asset Low Equity Funds shortlisted in this analysis is 1.37% p.a.

[35] Asset allocation and geographical allocation parameters still imply. However, smart-beta limitations, risk contribution per holding and tracking error parameters no longer apply.

Chapter 6: Conclusions, Recommendations and Limitations

6.1 Conclusion: Active vs Passive vs Smart-Beta

Prior, highly acclaimed literature regarding active, passive and smart-beta investment management styles provides mixed results. Internationally, financial markets tend to be more informationally efficient. Therefore, passive management should form the core of a well-diversified portfolio. Bogle (2010) states that he is a stronger believer in passive investing than he was when he created the first index fund in 1975. On the other hand, Clare, Motson and Thomas (2013) find evidence that an equally weighted portfolio of 1000 stocks selected by monkeys outperforms the market capitalisation index. US$100 invested at the beginning of 1968 would have achieved a terminal value of just under US$5000 if invested in the market capitalisation index, compared to just under US$9000 if invested in a randomly selected index of stocks that might as well have been chosen by monkeys.

Results surrounding market efficiency in South Africa are inconclusive as to whether the JSE can be considered efficient or not. Noakes and Rajaratnam (2016) along with Smith and Dyakova (2014) find that efficiency and non-efficiency for JSE listed stocks can be found in groups with similar attributes and characteristics such as size and liquidity on a stock-specific level. Emerging markets, including that of South Africa, present more significant opportunities for active managers to generate abnormal returns using their skill and informational edge. This study, therefore recommends and support the notion that investors should exploit the *"hot-hands effect"* by investing in active managers who consistently generate superior risk-adjusted returns.

The results from this study indicate that on an absolute basis, active managers from the following ASISA frameworks, (1) High Risk: SA General Equity, (2) Medium Risk: SA Multi-Asset High Equity and (3) Low Risk: SA Multi-Asset Low Equity, predominantly fail to outperform their benchmarks over the sample period (October 2009 – September 2019). However, this study recommends investors to exploit the *"hot-hands effect"* by identifying and shortlisting active managers who consistently prudence superior risk-adjusted returns versus their peers as measured by their Sharpe and Information Ratios.

The study recommends the use of RBSA as a secondary filter to identify active managers with the ability to add value over the passive asset classes and style indices they seek to replicate.

From the nine active managers, three from each ASISA framework who possess the *"hot-hands effect"*, not a single active manager managed to generate alpha over the passive asset classes and style indices they seek to replicate. Some active managers, however, manage to generate positive risk-adjusted returns with low correlation and low coefficients of determination compared to their benchmarks and shadow funds and was therefore considered. These metrics indicate the manager has the ability to generate returns while being agnostic of the composition of its benchmark or competitors. Additionally, a low R-squared indicate that active managers can identify and include alternative asset classes to generate returns, which justifies their active management fees.

For SA General Equity portfolios, investors should consider using active managers who invest in South African equities only. The study finds that active manager within South Africa has a competitive advantage when it comes to investing in South African companies only, and not companies listed on international exchanges. The offshore equity component of SA General Equity portfolios should consist solely of passive strategies such as Sygnia Itrix MSCI World Index ETF.

This study encourages investors to include passive building blocks and low-cost index funds within SA General Equity and SA Multi-Asset portfolios. The advantages of these holdings are threefold in that:

1. They reduce the total tracking of the portfolio, thus limiting active risk,
2. They reduce the total cost of the portfolio as measured by TIC, and,
3. It gives the investors exposure to a well-diversified portfolio of global or local securities at reduced costs,

Finally, the study confirms the findings of Arnott, Hsu and Moore (2005), fundamental index portfolios, or *"smart-beta"* are robust due to their mean-variance superiority compared to the market capitalisation-weighted index. Value factor, represented by A-DEX Value Fund, momentum factor, represented by A-DEX Momentum Fund and low volatility factor, represented by A-DEX Low Volatility Fund generated Sharpe Ratios superior to their active and passive counterparts. The study recommends the inclusion of A-DEX smart-beta funds to SA General Equity, SA Multi-Asset High Equity and SA Multi-Asset Low Equity portfolios. Not only do they reduce the overall cost as measured by the portfolio's TIC, but they also increase the aggregate risk-adjusted returns of the portfolio, measured by the Sharpe Ratio.

6.2 Conclusion: Low-Cost Core-Satellite Portfolios and Risk and Tracking Error Budgeting

The study develops a rule-based product range of low-cost core-satellite portfolios *"replica portfolios"* as initially proposed by Treynor and Black (1973). The idea behind the core-satellite portfolio is that the optimal portfolio must consist of a blend between active and passive components. This concept is later enhanced to incorporate risk and tracking error budgeting by Waring *et al*. (2000) and Amenc *et al*. (2004). Core-satellite obtains the optimal risky portfolio by blending the securities that are deemed inefficient *"active alpha"* with the efficient market index *"passive beta"*. This study extends the typical core-satellite portfolio to include active, passive and smart-beta holdings.

The study identifies three *"target portfolios"* from ASISA framework, namely:

1. High Risk: SA General Equity,
2. Medium Risk: SA Multi-Asset High Equity, and,
3. Low Risk: SA Multi-Asset Low Equity,

The study succeeds in bridging the gap between active, passive, and smart-beta investment management styles by introducing a low-cost portfolio construction technique, core-satellite portfolio management, which contributes to the risk and tracking error budgeting process.

Three unique products are developed during the final stage of this study, namely:

1. **High Risk: Fairtree Robo Core-Satellite Portfolio**
2. **Medium Risk: Investec Managed Robo Core-Satellite Portfolio**
3. **Low Risk: Old Mutual Real Income Robo Core-Satellite Portfolio**

Each product is suited to South African investors during various stages of their investment life cycle. The core-satellite product range this study develops is aligned with the findings of Cocco, Gomes, and Maenhout (2005) who evaluate the importance of portfolio and asset class choice over the life cycle of the investor. Moreover, the core-satellite product range supports the popular notion that the portfolio's share invested in equities should roughly decrease with age.

The results of the three unique core-satellite portfolios support the findings of Jorion (1992), that when investors have more assets at their disposal to choose from, a more widely diversified portfolio cannot generate returns less than a portfolio of fewer assets.

The core-satellite range of portfolios developed during this study had several implicit objectives that will be discussed throughout the following subsections.

6.2.1 Conclusion: Risk Budgeting with Core-Satellite

All three portfolios developed during this study were subject to robust multidimensional risk constraints, which include:

1. Risk mandate of each portfolio[36]
2. Total Risk budget of each portfolio[37], and,
3. Risk contribution per holding[38]

The study succeeds in meeting all of the above risk constraints. By implementing these rigorous risk constraints, all three portfolios have lower total risk compared to their benchmarks. Moreover, the high risk, **Fairtree Robo Core-Satellite Portfolio** incurs less total risk than the average actively managed SA General Equity Fund included in this study. The study, therefore, recommends a more significant allocation towards passive and smart-beta managers, compared to active managers. In contradiction to the above, the study finds that active managers within the SA Multi-Asset High Equity and SA Multi-Asset Low Equity classification can reduce the total risk of the portfolio. For this reason, the study recommends a more significant allocation to active managers when the risk mandate of the portfolio is medium to low.

6.2.2 Conclusion: Tracking Error Budgeting with Core-Satellite

By imposing a tracking error *TE* constraint on the product range of core-satellite portfolios, the study finds that there is a positive relationship between *TE* and absolute returns for all three portfolios. This objective, according to Roll (1992) is called the tracking error volatility (TEV) criterion. Investors who attempt to satisfy it fail to produce mean/variance efficient Makowitz portfolios. Active portfolios with low *TE's* will be dominated by portfolios with higher average

[36] Three unique risk profiles that are subject to ASISA's strategic asset allocation limitations along with PlexCrown SA Unit Trust Risk Classification Framework

[37] The maximum risk of each portfolio may not exceed the risk of its benchmark as measured by its annualised standard deviation.

[38] High- and medium risk portfolios are limited to a 35% risk contribution per holding, and low-risk portfolios are limited to a 30% risk contribution per holding.

returns, lower volatilities, but not necessarily lower *TE's.* Thus, Makowitz efficient frontier portfolios dominate *TE* efficient portfolios. This study confirms the research of Roll (1992). As *TE* increase, absolute returns increase, along with Sharpe Ratios, caused by allocation towards smart-beta strategies that have higher tracking errors, along with higher Sharpe Ratios.

Large institution investors who are cognisant of benchmarks returns over short time horizons are advised to use tracking error budgeting when constructing a portfolio of active, passive and smart-beta managers. Large allocations to passive managers will limit the extent of tracking error, however at the detriment of higher Sharpe Ratios. Investors with investment time horizons in excess of 40 years are encouraged to ignore tracking error budgeting and seek to invest in portfolios with maximum Sharpe Ratios only.

6.2.3 Conclusion: Fee Arbitrage with Core-Satellite

A primary motivation for the core-satellite portfolio is fee arbitrage. This study finds evidence to support the research of Amenc, Malaise and Martellini (2004) in that one can use core-satellite portfolios to reduce total fees, and in turn, generate higher alpha.

All three core-satellite portfolios developed during this study have lower total fees compared to the active only component included in the portfolio. The average fee reduction this study managed to achieve for high, medium and low-risk core-satellite products as measured by TIC versus active only portfolios is 1.91% p.a, 0.97% p.a. and 0.53% p.a. respectively. The fee reduction is most significant for the high-risk product since it has the largest allocation to passive and smart-beta managers. As total risk is reduced, a larger allocation towards active managers become quantifiable, and the fee reduction becomes diminishing.

The study recommends and strongly encourages investors to construct robust core-satellite portfolios with allocations to passive and smart-beta managers. Incremental allocations away from pure active managers will lead to fee arbitrage, and potentially more alpha over longer time horizons.

6.2.4 Conclusion: Returns with Core-Satellite

The study finds that by using core-satellite portfolios, investors can achieve multiple objectives. A result of core-satellite portfolios above from risk budgeting and fee arbitrage is its ability to increase absolute and risk-adjusted returns. The product range of three core-satellite portfolios developed during this study managed to achieve higher absolute and risk-adjusted returns compared to their benchmarks and active only counterparts.

On an absolute basis, the study finds that portfolios with larger equity allocations generate higher returns. As the equity allocation declines, the absolute return declines. Therefore, **Fairtree Robo Core-Satellite Portfolio** *(100% equity)* is the most preferred portfolio in absolute terms while **Old Mutual Real Income Core-Satellite Portfolio** *(40% equity)* is the least preferred in absolute terms.

The study finds that on a risk-adjusted performance basis, as measured by the Sharpe Ratio, the portfolio with the lowest equity allocation has the highest Sharpe Ratio. Therefore, **Old Mutual Real Income Core-Satellite Portfolio** *(40% equity)* is the most preferred portfolio as measured by its Sharpe Ratio. The study again recommends large institution investors, pension funds, and individuals who depend solely on the income of their portfolios to avoid a portfolio fully invested in equities. However, investors with investment time horizons in excess of 40 years are encouraged to focus on absolute returns, therefore being fully invested in equities.

6.3 Conclusion: Robo-Advisors Applying the Quantitative Methods

Compared to the US and the UK, where Robo-Advisors (RAs) have been hugely successful in recent years, South Africa’s RA market is still in its infancy. RAs are perhaps the most crucial disruptive trend in wealth and asset management, and it is estimated that around 49 percent of high net worth individuals globally would consider RAs to manage some portion of their total wealth (Beketov, Lehmann & Wittke, 2018).

This study evaluates several quantitative methods currently used by RAs globally and in South Africa. Surprisingly, the most popular quantitative method within RAs is Modern Portfolio Theory. These RAs seek to construct portfolios that are mean-variant efficient. This study employs rigorous quantitative techniques to construct a product range of low-cost portfolios and include:

1. Modern Portfolio Theory *(through Sharpe and Information Ratio filters)*
2. Returns Based Style Analysis
3. Multidimensional Risk Budgeting
4. Tracking Error Budgeting
5. Core-Satellite Portfolio Management
6. Fee Arbitrage

The study encourages RAs to develop robust, practical and sophisticated products that use the quantitative methods proposed in this paper. Not only will it provide cutting-edge financial advice, but it will also develop portfolios that clients are comfortable with.

The RA sector is expected to evolve dramatically over the next five to ten years. Companies who remain current in their offering, through the development of more sophisticated methodologies, which are aimed at producing superior returns and can be used as a marketing tool to attract new next-generation investors. This *"next-generation client"* is receptive to digital technologies, well educated, prefers to have active and ongoing control over their investments, and rely on the information from multiple online sources rather than an individual, human financial advisor. In turn, RAs who incorporate the methods proposed in this research can expect to attract higher AUM volumes.

6.4 Limitations of Research

All research studies can inevitably be improved.

This study uses prior, highly acclaimed literature and methodologies that form the cornerstone of modern finance and portfolio management. History cannot be changed, nor rewritten. Investment greats cited throughout this paper such as Harry Markowitz, Benjamin Graham, John Bogle, William Sharpe, Eugene Fama, Burton Malkiel and Warren Buffett each have their distinctive style or *"flavour"*. Throughout this research, the author made reference to notable quotes from investment greats which should form the cornerstone to any investment decision. The author cannot fault any method proposed by these greats.

This research, however, has the following limitations:

1. **Data Period:** Due to data limitations, this study only uses monthly data for a period of ten years (**October 2009 – September 2019)** which covers **120 months** of TR data. Over the past ten years, the South African economy, and particularly the JSE has experienced no significant market shock or recession such as the GFC. This period, however, displays unique, previously unwitnessed circumstances. In the first five years of the data period, 2009 - 2013, the FTSE/JSE All-Share J203T Index return an average of 20.36% per annum. The next five years tells an entirely different story as the average return for 2014 - 2018 was only 6.21% per annum. This research, for the reasons stated above, derived a conclusion using data for the period **October 2009 – September 2019.** Using more extended periods of data might enhance the results in the future.

2. **Data Sample:** The primary aim of this study was to develop core-satellite portfolios using active, passive and smart-beta funds. This study, however, narrowed the available active managers down by eliminating active managers who did not have a performance track record of at least four years of sufficient assets under management. The study identifies a total of 574 actively managed unit trusts, with a combined AUM of R1,13 trillion. The study uses a sample of 61 active managers with a combined AUM of R904 532 million, representing 79.46% of all active funds from the ASISA framework covered in this study. The accuracy and validity of this study can be improved by including a higher percentage of AUM as part of the data sample.

3. **Tax Implications:** This study recommends the use of core-satellite portfolios with different risk profiles, suited to different types of South African investors. The core-satellite portfolios developed during this study consists of several asset classes which might have different tax implications. Although the tax implications are beyond the scope of this study, the author wishes to advise investors that returns may be affected by their tax status, age and level of income.

The abovementioned limitations are in no manner insoluble and will enhance the validity of this study if addressed in future research.

6.5 Recommendations for Future Research

This study encompasses several disciplines of academic literature which can be explored in future research. Further research will traverse not only a single disciple, but can embody:

Finance: This study focuses solely on South African core-satellite portfolios (i.e. portfolios that need to invest approximately 70 percent of their assets within South Africa). The product range of core-satellite portfolios developed in this study consists only of active, passive and smart-beta strategies. Further research can investigate the implications of core-satellite portfolios when investing in global financial markets. The South African stock market, represented by the JSE, is currently ranked the 19th largest stock exchange in the world by market capitalisation. Constructing core-satellite portfolios of global assets could yield divergent results to those found in this study. Additionally, further research could evaluate the risk, tracking error, fee and performance effect of including alternative assets and asset classes such as hedge funds, private equity, venture capital, private debt, structured products, infrastructure and natural resources within the core-satellite portfolio.

Financial Planning and Behavioural Finance: By determining a client's future value of liabilities, probability of occurrence and financial biases, further research can develop a low-cost outcome-based core-satellite portfolio. These portfolios cover the liability as it occurs, while generating returns above inflation-adjusted future liability values. There is a parallel link between the success of portfolios developed by Robo-advisors and the behavioural inputs required to meet the needs and desires of the client. Further research in this field would make the quantitative methods proposed in this paper tangible.

Computer Science: The success of Robo-advisors and the portfolios they propose to clients rely on the algorithms and programs developed within the field of computer science. The ability to process, store and manipulate data will pave the way of the next generation of RAs. Although beyond the scope of this study, further research within the field of computer science, computational science and big data with regards to the algorithms within RAs would be indispensable. Writing robust algorithms to match a client's risk and future liabilities to prudent core-satellite portfolios with multidimensional risk budgets, tracking error budgets and asset class constraints is paramount.

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Annexure A: SA General Equity Funds Per AUM Bracket at 30 June 2019

SA General Equity Funds at 30 June 2019 *(10 Billion < ZAR < 40 Billion) ~ 6 funds*		
FUND	**AUM**	**INCEPTION DATE**
Allan Gray Equity Fund	R38 724 Billion	Oct-98
Coronation Top 20 Fund	R19 942 Billion	Oct-00
Old Mutual Investors Fund	R13 253 Billion	Oct-66
Fairtree Equity Prescient Fund	R11 680 Billion	Nov-11
Nedgroup Investments Rainmaker Fund	R11 251 Billion	Jun-00
Abax Equity Prescient Fund	R10 450 Billion	Oct-04
	R105 301 Billion	

SA General Equity Funds at 30 June 2019 *(5 Billion < ZAR < 10 Billion) ~ 8 funds*		
FUND	**AUM**	**INCEPTION DATE**
Stanlib Multi Manager Equity Fund	R9 666 Billion	Oct-98
Investec Equity Fund	R9 162 Billion	Nov-87
PSG Wealth Creator FOF	R7 797 Billion	Jun-09
Sanlam (SIM) General Equity Fund	R7 503 Billion	Aug-05
Coronation Equity Fund	R7 138 Billion	Apr-96
Foord Equity Fund	R6 359 Billion	Sep-02
Oasis Crescent Equity Fund	R5 513 Billion	Jul-98
PortfolioMetrix BCI Equity FOF	R5 298 Billion	Jul-14
	R58 436 Billion	

SA General Equity Funds at 30 June 2019 *(0 Billion < ZAR < 5 Billion) ~ 10 funds*		
FUND	**AUM**	**INCEPTION DATE**
PSG Equity Fund	R4 739 Billion	Dec-97
Prudential Dividend Maximiser Fund	R4 281 Billion	Aug-99
Stanlib Equity Fund	R4 156 Billion	Jan-70
Investec Value Fund	R3 919 Billion	May-97
Marriott Dividend Growth Fund	R3 860 Billion	Aug-88
Prudential Equity Fund	R3 442 Billion	Aug-99
Allan Gray SA Equity Fund	R3 004 Billion	Mar-15
Stanlib SA Equity Fund	R2 929 Billion	Aug-94
Discovery Equity Fund	R2 915 Billion	Nov-07
Absa Select Equity Fund	R2 629 Billion	Mar-13
	R35 875 Billion	

Annexure B: SA Multi-Asset High Equity Funds Per AUM Bracket at 30 June 2019

SA Multi Asset High Equity Funds at 30 June 2019 *(20 Billion < ZAR < 151 Billion) ~ 7 funds*		
FUND	**AUM**	**INCEPTION DATE**
Allan Gray Balanced Fund	R150 563 Billion	Oct-99
Coronation Balanced Plus Fund	R88 990 Billion	Apr-96
Investec Opportunity Fund	R44 372 Billion	May-97
Foord Balanced Fund	R30 173 Billion	Sep-02
Discovery Balanced Fund	R26 625 Billion	Nov-07
Prudential Balanced Fund	R23 201 Billion	Aug-99
PSG Wealth Moderate FOF	R20 652 Billion	Dec-08
	R384 576 Billion	
SA Multi Asset High Equity Funds at 30 June 2019 *(10 Billion < ZAR < 20 Billion) ~ 5 funds*		
FUND	**AUM**	**INCEPTION DATE**
Sanlam (SIM) Balanced Fund	R18 649 Billion	Feb-95
Old Mutual Balanced Fund	R17 963 Billion	Mar-94
Investec Managed Fund	R15 384 Billion	Feb-94
Old Mutual Multi-Managers Balanced FOF	R13 574 Billion	Jun-01
PSG Balanced Fund	R11 795 Billion	Sep-13
	R77 365 Billion	
SA Multi Asset High Equity Funds at 30 June 2019 *(2 Billion < ZAR < 10 Billion) ~ 11 funds*		
FUND	**AUM**	**INCEPTION DATE**
Stanlib Multi-Manager Balanced Fund	R6 389 Billion	Jan-02
Rezco Value Trend Fund	R5 028 Billion	Sep-04
Satrix Balanced Index Fund	R4 303 Billion	Oct-13
Stanlib Balanced Fund	R4 216 Billion	Aug-94
Marriott Balanced FOF	R2 629 Billion	Oct-01
Sanlam Multi-Managed Balanced FOF	R2 317 Billion	Mar-99
Alexander Forbes Performer Managed Unit Trust	R2 287 Billion	Jan-11
Sasfin BCI Prudential Fund	R2 188 Billion	Jan-13
Sygnia CPI +6% Fund	R2 061 Billion	Jun-12
PPS Balanced FOF	R2 058 Billion	Jul-11
Absa Multi-Managed Growth FOF	R2 048 Billion	Feb-07
	R35 523 Billion	

Annexure C: SA Multi-Asset Low Equity Funds Per AUM Bracket at 30 June 2019

SA Multi Asset Low Equity Funds at 30 June 2019 *(20 Billion < ZAR < 55 Billion) ~ 3 funds*		
FUND	**AUM**	**INCEPTION DATE**
Allan Gray Stable Fund	R50 867 Billion	Jul-00
Coronation Balanced Defensive Fund	R33 208 Billion	Feb-07
Prudential Inflation Plus Fund	R32 536 Billion	Jun-01
	R116 611 Billion	
SA Multi Asset Low Equity Funds at 30 June 2019 *(10 Billion < ZAR < 20 Billion) ~ 4 funds*		
FUND	**AUM**	**INCEPTION DATE**
Nedgroup Investments Stable Fund	R19 509 Billion	Jul-11
Sanlam (SIM) Inflation Plus Fund	R13 345 Billion	Apr-99
PSG Wealth Preserver FOF	R10 691 Billion	Jun-09
Investec Cautious Managed Fund	R10 162 Billion	Apr-06
	R53 706 Billion	
SA Multi Asset Low Equity Funds at 30 June 2019 *(2 Billion < ZAR < 10 Billion) ~ 7 funds*		
FUND	**AUM**	**INCEPTION DATE**
Stanlib Balanced Cautious Fund	R6 959 Billion	Jan-09
Old Mutual Stable Growth Fund	R6 432 Billion	Jul-07
Absa Absolute Fund	R5 835 Billion	Nov-06
Old Mutual Real Income Fund	R5 434 Billion	Apr-06
PSG Stable Fund	R4 617 Billion	Sep-11
Absa Multi-Managed Preserver FOF	R3 472 Billion	Feb-07
Personal Trust Conservative Managed Fund	R3 121 Billion	Aug-08
	R35 807 Billion	

Annexure D: Index Funds and ETF's

SA Equity Passive		
NAME	**AUM (30/06/2019)**	**TR DATA DATES**
Satrix ALSI Index Fund	R717 Million	Feb 2013 - Sep 2019
STANLIB ALSI 40 Fund	R829 Million	Oct 2009 - Sep 2019

Global Equity Passive		
NAME	**AUM (30/06/2019)**	**TR DATA DATES**
Sygnia Itrix MSCI World Index ETF	R8 015 Billion	Oct 2009 - Sep 2019

SA Bond Passive		
NAME	**AUM (30/06/2019)**	**TR DATA DATES**
Sygnia All Bond Index Fund	R671 Million	Mar 2015 - Sep 2019

SA Income Passive		
NAME	**AUM (30/06/2019)**	**TR DATA DATES**
Nedgroup Investments Core Income Fund	R45 645 Billion	Oct 2009 - Sep 2019

Annexure E: Benchmarks

SA Equity Benchmarks	
NAME	**TR DATA DATES**
FTSE/JSE All Share (J203T)	Oct 2009 - Sep 2019
PlexCrown SA Equity General Index	Oct 2009 - Sep 2019

Global Equity Benchmarks	
NAME	**TR DATA DATES**
MSCI AC World (ZAR TR)	Oct 2009 - Sep 2019

SA Multi-Asset Benchmarks	
NAME	**TR DATA DATES**
75% FTSE/JSE All Share index (J203T) + 25% JSE/ASSA All Bond Index (ALBI)	Oct 2009 - Sep 2019
40% FTSE/JSE All Share index (J203T) + 40% ALBI + 20% STeFI Composite index	Oct 2009 - Sep 2019
PlexCrown SA Multi Asset High Equity Index	Oct 2009 - Sep 2019
PlexCrown SA Multi Asset Low Equity Index	Oct 2009 - Sep 2019

Annexure F: A-DEX Momentum, Value and Low Volatility Fund Factsheets

1 May 2019

Key Information:

Asset Class
South African Listed Equity
Benchmark
FTSE/JSE SWIX Total Return Index
Fund Category
Active Beta Building Block

Risk
High (H)

L	LM	M	MH	H
				●

Fund Manager:

Prof Paul van Rensburg

SalientQuants (Pty) Ltd
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Bespoke Client Research:

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With operational support from:

LEGAE PERESEC

Leagae Peresec Fund Platform
6A Sundown Valley Crescent
Sandown, Sandton, 2196
South Africa

A-DEX Investment Toolkit — Risk Optimised Momentum Fund

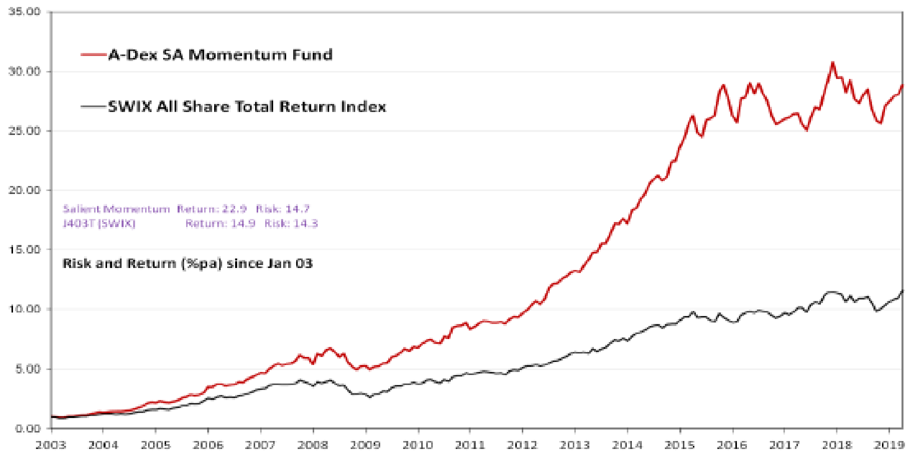
Fund Description and Objective:

The A-Dex Risk Optimized Momentum Fund is constructed through a pre-defined rules-based strategy that employs filters, a multi-variate signal and risk optimization to select and weigh stocks. It consists of a set of stocks chosen from approximately the 60 largest and most liquid stocks listed on the JSE. In this manner, the Momentum effect in share price returns is offered to investors in a low cost and risk optimized form that is designed to lessen the impact of momentum crashes.

The Salient Portfolio Toolkit® and Role of Active Indices in Portfolio Construction

The **Salient SA Portfolio Toolkit®** comprises three essential Active Index equity building blocks: (i) a **Low Volatility Index** (that exploits diversification and the lack of higher returns to higher volatility shares); (ii) a **Value Index** (that systematically buys 'cheap' shares that are good quality) and, its counterpart; (iii) a **Momentum Index** (that systematically purchases high momentum shares in a risk controlled framework). Combining these rules-based funds allows for inexpensive, diversified, liquid and transparent investment portfolios that are void of style-drift or manager risk and explicitly customized to the client's needs. A cloud-based risk allocation tool, the A-Dex Prism, which uses these (or user selected) constituents is available at http://toolkit.salientquants.com.

Performance Graph and Salient Facts:



	A-Dex MM Fund	SWIX ALSI (TRI)		A-Dex MM Fund	SWIX ALSI
1 Month Return	2.65%	5.41%	Dividend Yield	4.51%	3.48%
3 Month Return	4.96%	8.40%	Earnings Yield	7.01%	5.30%
6 Month Return	11.38%	17.62%	Price:Book Ratio	3.04	1.92
12 Month Return	-1.50%	3.70%	1 Year Momentum	5.88%	8.21%
Risk (p.a.)	11.80%	11.21%	Sales Growth	9.20%	8.37%

1 May 2019

Salient SA Value Fund

Key Information:

Asset Class

South African Listed Equity

Benchmark

FTSE/JSE SWIX Total Return Index

Fund Category

Low Cost Active Beta Building Block

Risk

High (H)

L	LM	M	MH	H
				●

Fund Manager:

Prof Paul van Rensburg

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Bespoke Client Research:

Carl Isernhinke

Head of Client Solutions
Carl@icon.co.za

+ 27 83 325 9763

With operational support from:

LEGAE PERESEC

Leagae Peresec Fund Platform
6A Sundown Valley Crescent
Sandown, Sandton, 2196
South Africa

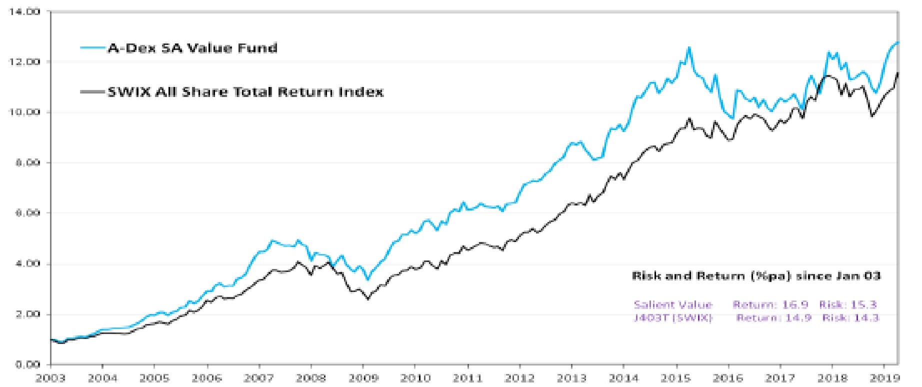
Fund Description and Objective:

The Salient Value Index Fund tracks the proprietary Salient Value Index. It is constructed through a pre-defined rules-based strategy to select and weight stocks on their degree of cheapness as measured by price relative to a composite of headline earnings, book value and dividends. It consists of a set of 25-30 stocks chosen from the 60 largest and most liquid stocks listed on the JSE. In this manner, the Value effect in share price returns is offered in a low cost indexed form.

The Salient Portfolio Toolkit® and Role of Active Indices in Portfolio Construction

The **Salient SA Portfolio Toolkit®** comprises three essential Active Index equity building blocks: (i) a **Low Volatility Index** (that exploits diversification and the lack of higher returns to higher volatility shares); (ii) a **Value Index** (that systematically buys 'cheap' shares that are good quality) and, its counterpart; (iii) a **Momentum Index** (that systematically purchases high momentum shares in a risk controlled framework). Combining these rules-based funds allows for inexpensive, diversified, liquid and transparent investment portfolios that are void of style-drift or manager risk and explicitly customized to the client's needs. A cloud-based risk allocation tool, the A-Dex Prism, which uses these (or user selected) constituents is available at http://toolkit.salientquants.com

Performance Graph and Salient Facts:



	Salient Value Fund	*SWIX ALSI (TRI)*		*Salient Value Fund*	*SWIX ALSI*
1 Month Return	1.06%	5.41%	Dividend Yield	4.28%	3.48%
3 Month Return	7.27%	8.40%	Earnings Yield	7.67%	5.30%
6 Month Return	16.06%	17.62%	Price:Book Ratio	1.62	1.92
12 Month Return	6.79%	3.70%	1 Year Momentum	1.11%	8.21%
Risk (p.a.)	12.80%	11.21%	Sales Growth	5.52%	8.37%

1 May 2019

Key Information:

Asset Class
South African Listed Equity
Benchmark
FTSE/JSE SWIX Total Return Index
Fund Category
Low Cost Active Beta Building Block

Risk

High (H)

L	LM	M	MH	H
				●

Fund Manager:

Prof Paul van Rensburg

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Bespoke Client Research:

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Head of Client Solutions
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+ 27 83 325 9763

With operational support from:

LEGAE PERESEC

Leagae Peresec Fund Platform
6A Sundown Valley Crescent
Sandown, Sandton, 2196
South Africa

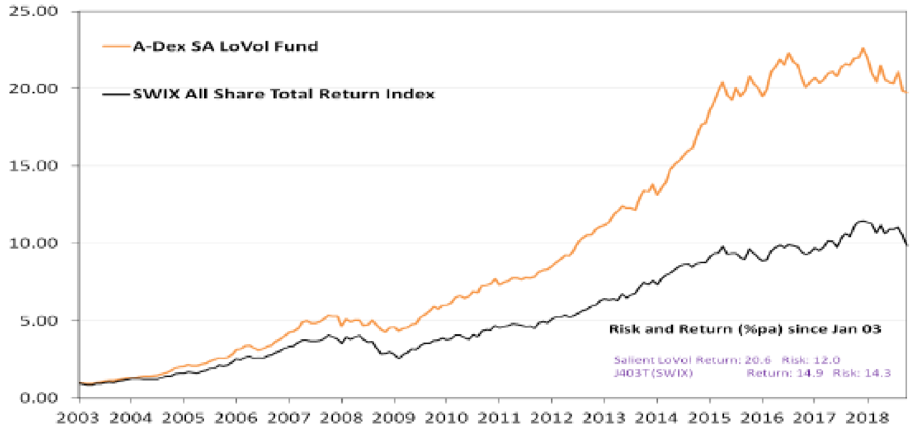
Fund Description and Objective:

The Salient Low Volatility Fund tracks the proprietary Salient Low Volatility Index. It is constructed through a pre-defined rules-based strategy to select and weight stocks so as to achieve the lowest risk possible for the overall equity based fund. It consists of a diversified set of stocks chosen from the 60 largest and most liquid shares listed on the JSE. In this manner, the Equity Market Premium in asset class returns is offered to investors both at low risk and low cost.

The Salient Portfolio Toolkit® and Role of Active Indices in Portfolio Construction

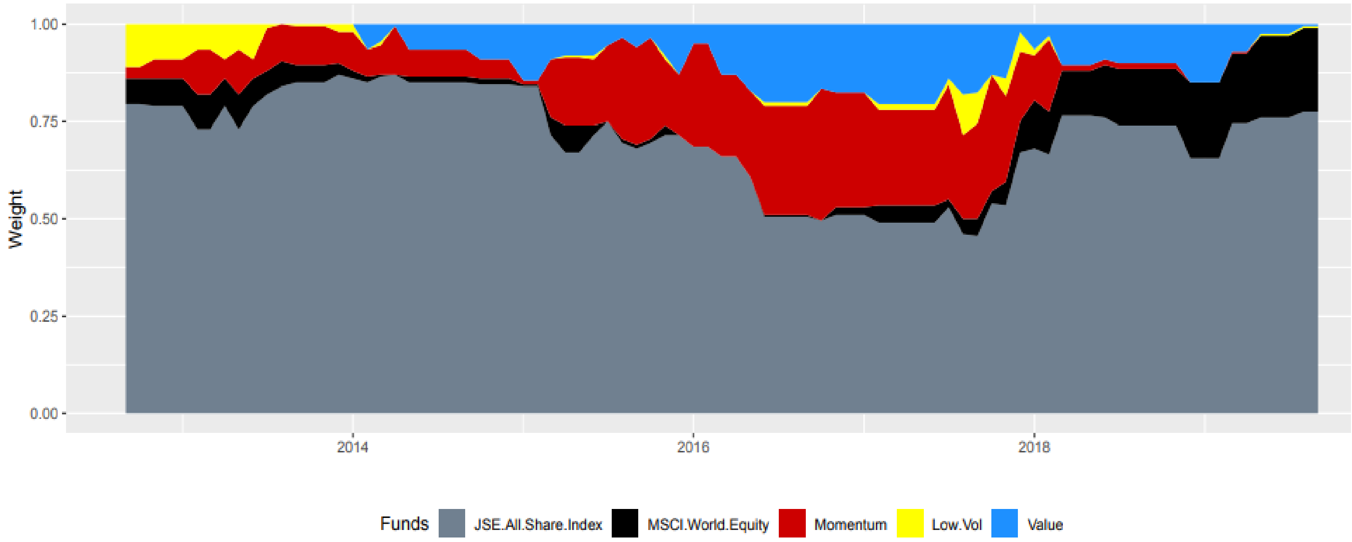
The **Salient SA Portfolio Toolkit®** comprises three essential Active Index equity building blocks: (i) a **Low Volatility Index** (that exploits diversification and the lack of higher returns to higher volatility shares); (ii) a **Value Index** (that systematically buys 'cheap' shares that are good quality) and, its counterpart; (iii) a **Momentum Index** (that systematically purchases high momentum shares in a risk controlled framework). Combining these rules-based funds allows for inexpensive, diversified, liquid and transparent investment portfolios that are void of style-drift or manager risk and explicitly customized to the client's needs. A cloud-based risk allocation tool, the A-Dex Prism, which uses these (or user selected) constituents is available at http://toolkit.salientquants.com.

Performance Graph and Salient Facts:



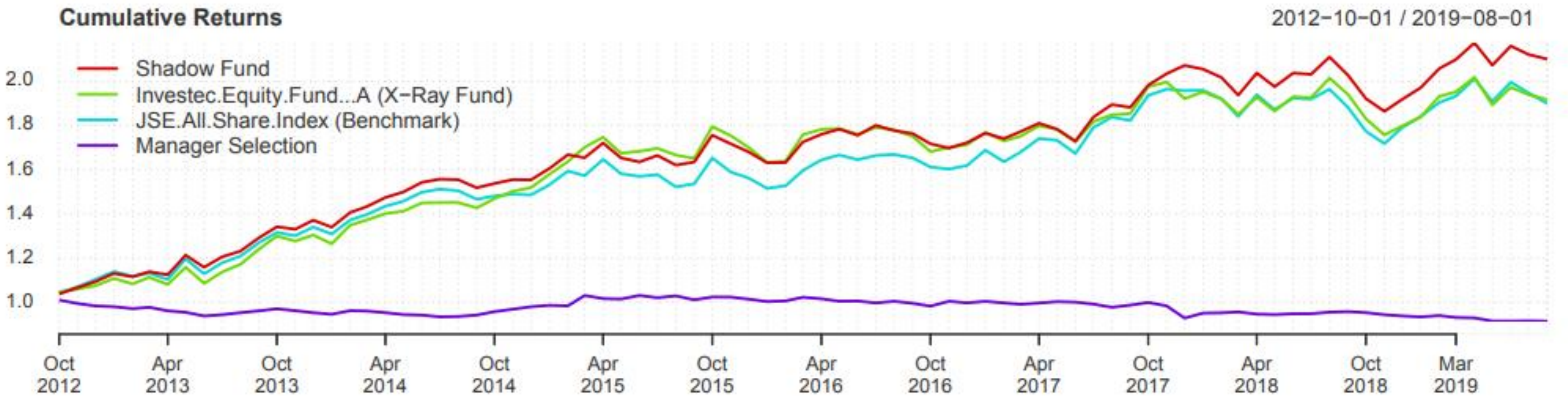
	Salient Low Vol Fund	*SWIX ALSI (TRI)*
1 Month Return	2.62%	5.41%
3 Month Return	3.02%	8.40%
6 Month Return	3.28%	17.62%
12 Month Return	-5.12%	3.70%
Mean Return (p.a)	20.39%	11.21%
Mean Risk (p.a)	12.01%	

Annexure G: X-RAY Investec Equity Fund



Building Blocks :

Name	Min Weight	Max Weight	Final Weight
JSE All-Share Index	0	100	77.5
Low Vol	0	100	0.5
Momentum	0	100	0.0
MSCI World Equity	0	100	21.5
Value	0	100	0.5



Investec Equity Fund X-RAY Results

X-RAY Results of Investec Equity Fund (1 Sep 2012 – 1 Sep 2019)

	Annualised Return (%)	Annualised Std Dev (%)	Annualised Sharpe Ratio
Investec Equity Fund	9.87	11.53	0.86
Shadow Fund	11.33	10.39	1.09
Fund to Benchmark	0.15	4.51	**0.02**
Fund to Shadow	-1.46	4.41	**-0.29**
FTSE/JSE All Share (J203T)	9.72	11.2	0.87
MSCI AC World (ZAR TR)	19.45	14.59	1.33
Momentum	12.28	11.61	1.06
Low Volatility	10.09	9.79	1.03
Value	15.48	12.72	1.22

Summary and Correlations Results of Investec Equity Fund

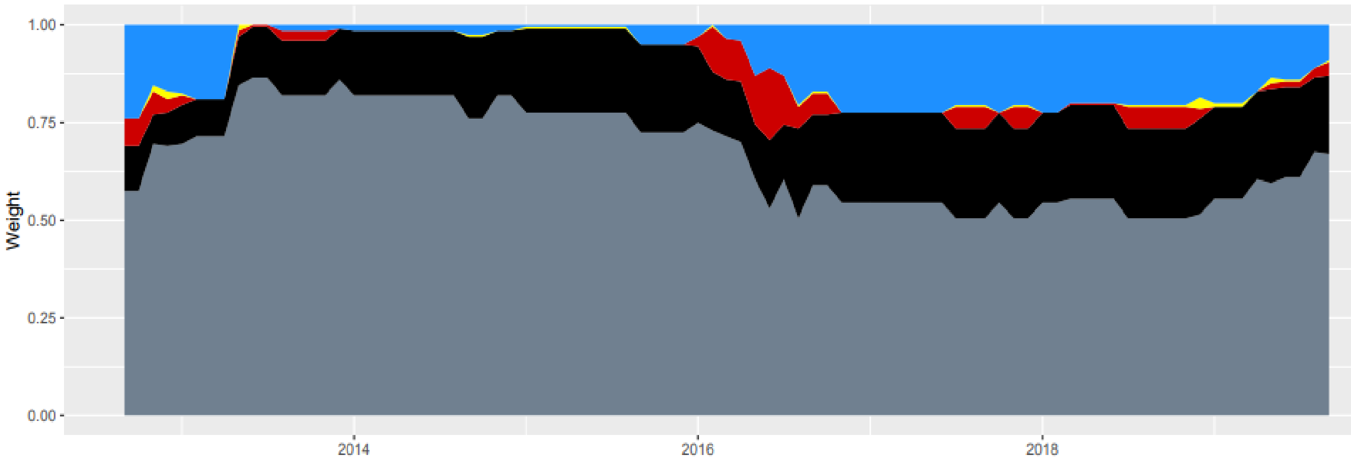
Fund to Shadow		Fund to Benchmark	
Alpha (% p.a.)	**-1.29**	Alpha (% p.a.)	-0.13
R-Squared	**0.85**	R-Squared	0.88
Correlation	0.92	Correlation	0.94
Tracking Error (% p.a.)	4.41	Tracking Error (% p.a.)	4.09

From the X-RAY results of Investec Equity Fund, we find that the fund outperforms the benchmark (FTSE/JSE All Share (J203T)) on an absolute basis over the period 1 September 2012 – 1 September 2019. Investec Equity Fund, however fails to outperforms the benchmark (FTSE/JSE All Share (J203T)) on a risk-adjusted basis as the annualised Sharpe Ratio of the fund is 0.86, compared to the annualised Sharpe Ratio of the FTSE/JSE All Share (J203T) of 0.87.

Comparing Investec Equity Fund to its shadow fund, which consists out of the following passive asset classes and style indices: **77.5% FTSE/JSE All Share, 21.5% MSCI World Equity, 0.5% Value** and **0.5% Low Volatility**, the fund fails to outperform on an absolute and risk-adjusted basis. The majority of the variations of returns of Investec Equity Fund can be explained by the holdings of the shadow fund, since the R-squared is 0.85. The annualised alpha of Investec Equity Fund versus the shadow fund is -1.29, which means the fund materially failed to add value over the passive asset classes and style indices it seeks to replicate.

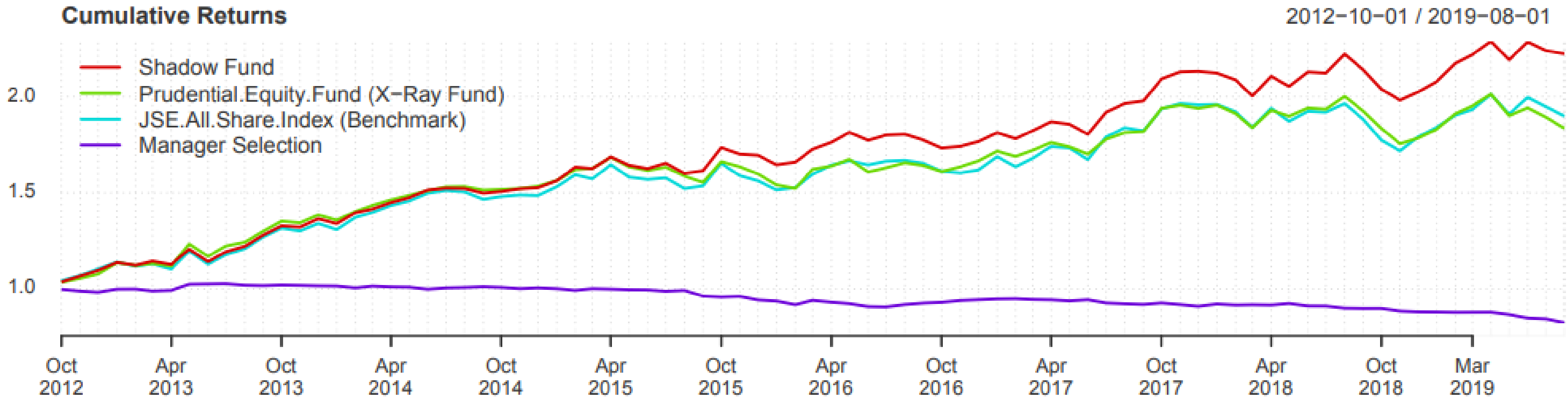
Investec Equity Fund, compared to Fairtree Equity Prescient Fund is less likely to outperform the passive asset classes and style indices it seeks to replicate. This is most likely due to the fact that Investec Equity Fund invests a large portion of its assets in global equities. The fund manager may not have a competitive advantage when it comes to investing in global equities.

Annexure H: X-RAY Prudential Equity Fund



Building Blocks :

Name	Min Weight	Max Weight	Final Weight
JSE All-Share Index	0	100	67.0
Low Vol	0	100	0.5
Momentum	0	100	3.5
MSCI World Equity	0	100	20.0
Value	0	100	9.0



Prudential Equity Fund X-RAY Results

X-RAY Results of Prudential Equity Fund (1 Sep 2012 – 1 Sep 2019)

	Annualised Return (%)	**Annualised Std Dev (%)**	**Annualised Sharpe Ratio**
Prudential Equity Fund	9.18	10.5	0.87
Shadow Fund	12.25	9.92	1.24
Fund to Benchmark	-0.54	4.08	**-0.16**
Fund to Shadow	-3.07	3.43	**-0.81**
FTSE/JSE All Share (J203T)	9.72	11.2	0.87
MSCI AC World (ZAR TR)	19.45	14.59	1.33
Momentum	12.28	11.61	1.06
Low Volatility	10.09	9.79	1.03
Value	15.48	12.72	1.22

Summary and Correlations Results of Prudential Equity Fund

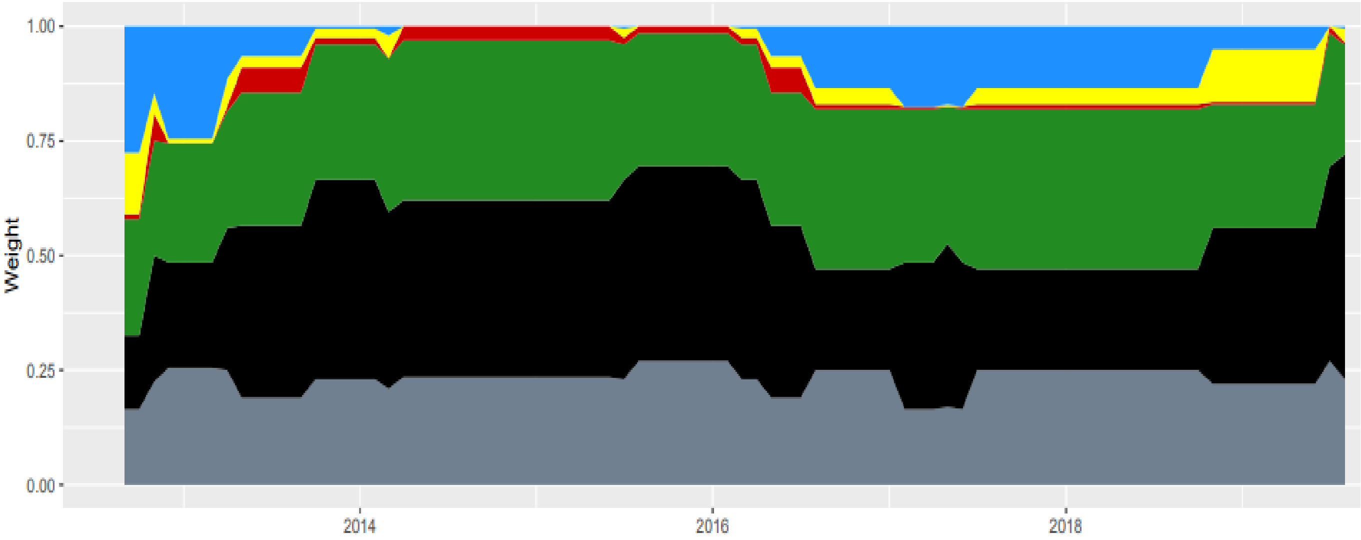
Fund to Shadow		**Fund to Benchmark**	
Alpha (% p.a.)	**-2.76**	Alpha (% p.a.)	-0.44
R-Squared	**0.89**	R-Squared	0.89
Correlation	0.95	Correlation	0.95
Tracking Error (% p.a.)	3.43	Tracking Error (% p.a.)	3.86

From the X-RAY results of Prudential Equity Fund, we find that the fund fails to outperform the benchmark (FTSE/JSE All Share (J203T)) on an absolute basis over the period 1 September 2012 – 1 September 2019. Prudential Equity Fund, however takes less risk than the benchmark and therefore the annualised Sharpe Ratio of the fund is 0.87, which is the same the annualised Sharpe Ratio of the FTSE/JSE All Share (J203T) of 0.87.

Comparing Prudential Equity Fund to its shadow fund, which consists out of the following passive asset classes and style indices: **67% FTSE/JSE All Share, 20% MSCI World Equity, 9% Value, 0.5% Low Volatility** and **3.5% Momentum**, the fund fails to outperform on an absolute and risk-adjusted basis. The majority of the variations of returns of Prudential Equity Fund can be explained by the holdings of the shadow fund, since the R-squared is 0.89. The annualised alpha of Prudential Equity Fund versus the shadow fund is -2.76, which means the fund materially failed to add value over the passive asset classes and style indices it seeks to replicate.

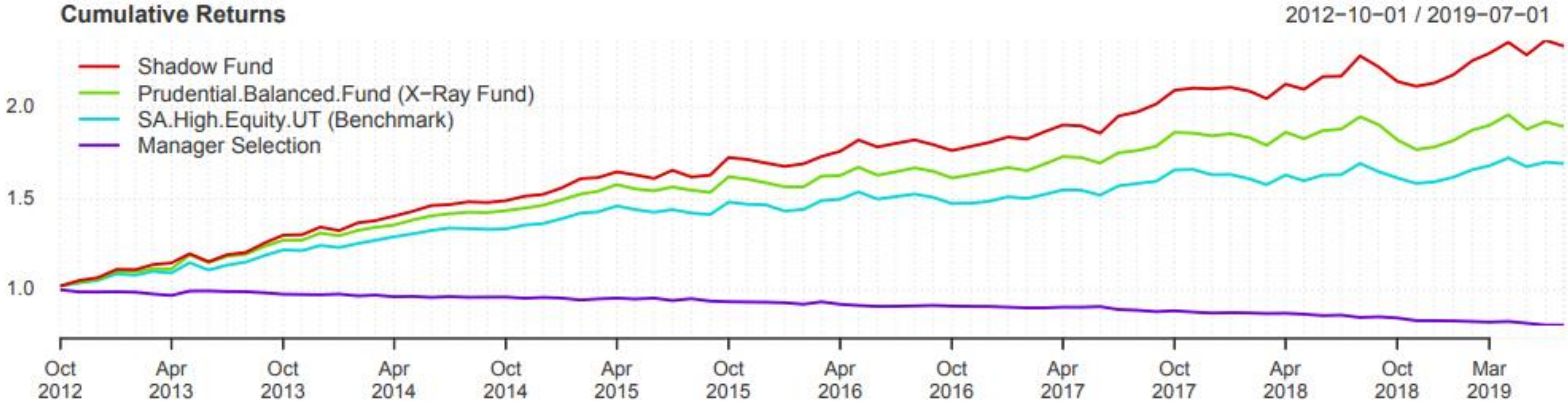
Prudential Equity Fund, compared to Fairtree Equity Prescient Fund is less likely to outperform the passive asset classes and style indices it seeks to replicate. This is most likely also due to the fact that Prudential Equity Fund, like Investec Equity Fund, invests a large portion of its assets in global equities. The fund manager may not have a competitive advantage when it comes to investing in global equities.

Annexure I: X-RAY Prudential Balanced Fund



Building Blocks :

Name	Min Weight	Max Weight	Final Weight
ALBI	0	100	23.0
JSE All-Share Index	0	100	49.0
Low Vol	0	100	3.0
Momentum	0	100	0.5
MSCI World Equity	0	100	24.0
Value	0	100	0.5



Prudential Balanced Fund X-RAY Results

X-RAY Results of Prudential Balanced Fund (1 Sep 2012 – 1 Sep 2019)

	Annualised Return (%)	Annualised Std Dev (%)	Annualised Sharpe Ratio
Prudential Balanced Fund	9.82	7.42	1.32
Shadow Fund	13.23	7.37	1.8
Fund to Benchmark	1.8	2.03	**0.85**
Fund to Shadow	-3.41	2.42	**-1.27**
Benchmark (SA High Equity UT)	8.02	6.46	1.24
FTSE/JSE All Share (J203T)	10.25	11.2	0.92
MSCI AC World (ZAR TR)	18.92	14.63	1.29
ALBI	7.34	7.56	0.97
Momentum	12.89	11.6	1.11
Low Volatility	10.07	9.85	1.02
Value	15.95	12.75	1.25

Summary and Correlations Results of Prudential Balanced Fund

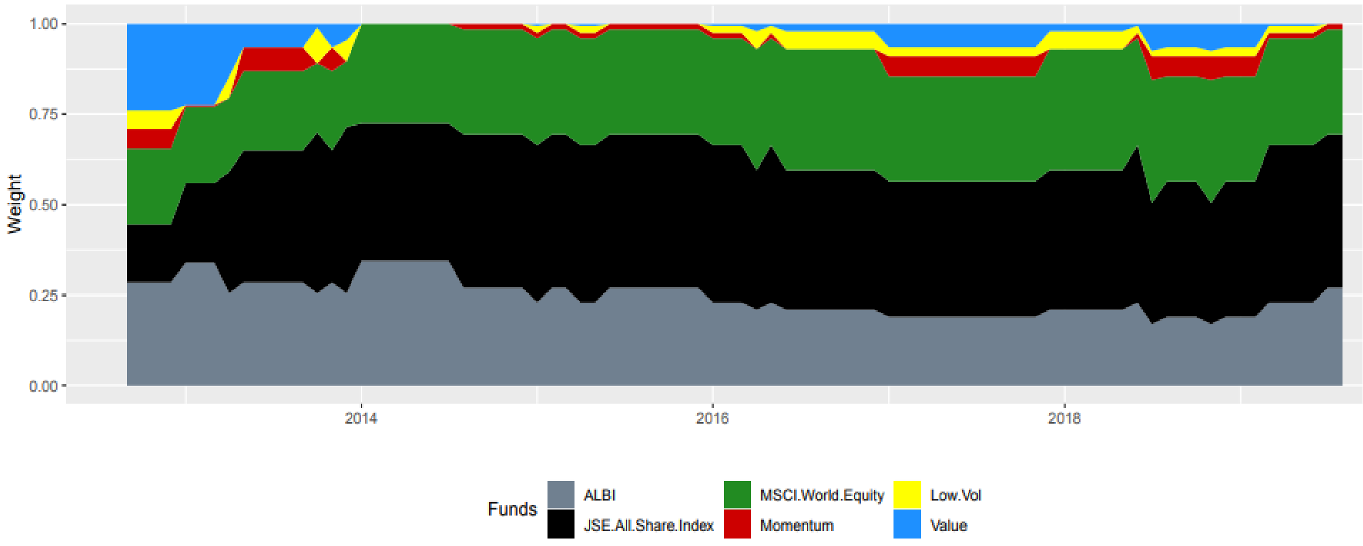
Fund to Shadow		Fund to Benchmark	
Alpha (% p.a.)	**-3.07**	Alpha (% p.a.)	1.95
R-Squared	**0.9**	R-Squared	0.93
Correlation	0.95	Correlation	0.96
Tracking Error (% p.a.)	2.42	Tracking Error (% p.a.)	2.41

From the X-RAY results of Prudential Balanced Fund, we find that the fund outperforms the benchmark (SA High Equity UT Sector) on an absolute basis over the period 1 September 2012 – 1 September 2019. Prudential Balanced Fund also outperforms the benchmark (SA High Equity UT Sector) on a risk-adjusted basis as the annualised Sharpe Ratio of the fund is 1.32, compared to the annualised Sharpe Ratio of the SA High Equity UT Sector of 1.24.

Comparing Prudential Balanced Fund to its shadow fund, which consists out of the following passive asset classes and style indices: **49% FTSE/JSE All Share, 23% ALBI, 24% MSCI World Equity, 0.5% Value, 3% Low Volatility** and **0.5% Momentum**, the fund fails to outperform on an absolute and risk-adjusted basis. The majority of the variations of returns of Prudential Balanced Fund can be explained by the holdings of the shadow fund, since the R-squared is 0.90.

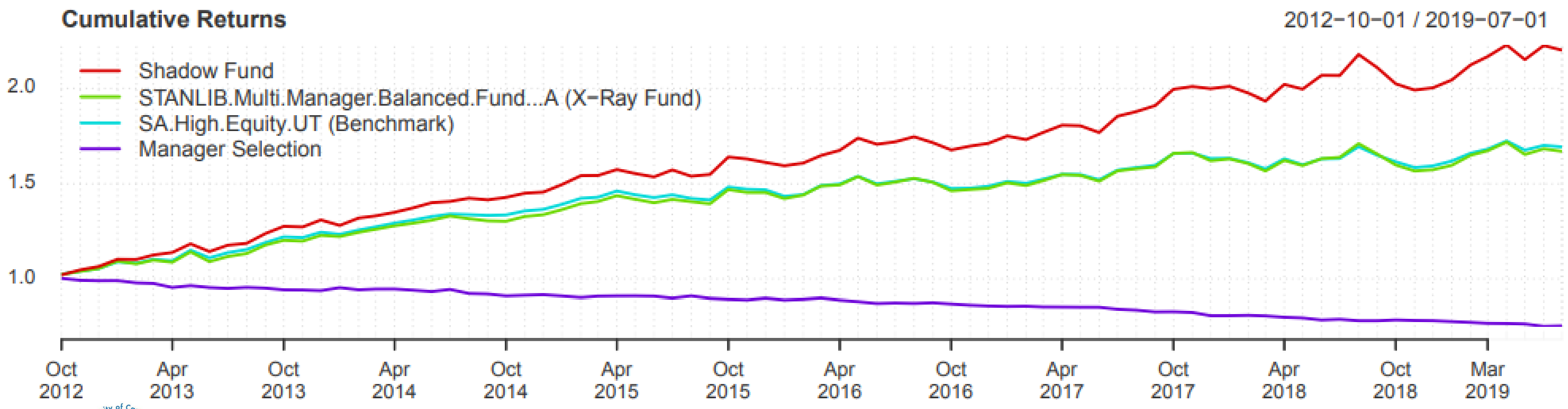
The annualised alpha of Prudential Balanced Fund versus the shadow fund is -3.07%, which means the fund materially failed to add value over the passive asset classes and style indices it seeks to replicate.

Annexure J: X-RAY Stanlib Multi Manager Balanced Fund



Building Blocks :

Name	Min Weight	Max Weight	Final Weight
ALBI	0	100	27.0
JSE All-Share Index	0	100	42.5
Low Vol	0	100	0.0
Momentum	0	100	1.5
MSCI World Equity	0	100	29.0
Value	0	100	0.0



Stanlib Multi Manager Balanced Fund X-RAY Results

X-RAY Results of Stanlib Multi Manager Balanced Fund (1 Sep 2012 – 1 Sep 2019)

	Annualised Return (%)	**Annualised Std Dev (%)**	**Annualised Sharpe Ratio**
Stanlib Multi Manager Balanced Fund	7.8	7.36	1.06
Shadow Fund	12.23	7.63	1.6
Fund to Benchmark	-0.22	1.44	**-0.11**
Fund to Shadow	-4.43	2.66	**-1.52**
Benchmark (SA High Equity UT)	8.02	6.46	1.24
FTSE/JSE All Share (J203T)	10.25	11.2	0.92
MSCI AC World (ZAR TR)	18.92	14.63	1.29
ALBI	7.34	7.56	0.97
Momentum	12.89	11.6	1.11
Low Volatility	10.07	9.85	1.02
Value	15.95	12.75	1.25

Summary and Correlations Results of Stanlib Multi Manager Balanced Fund

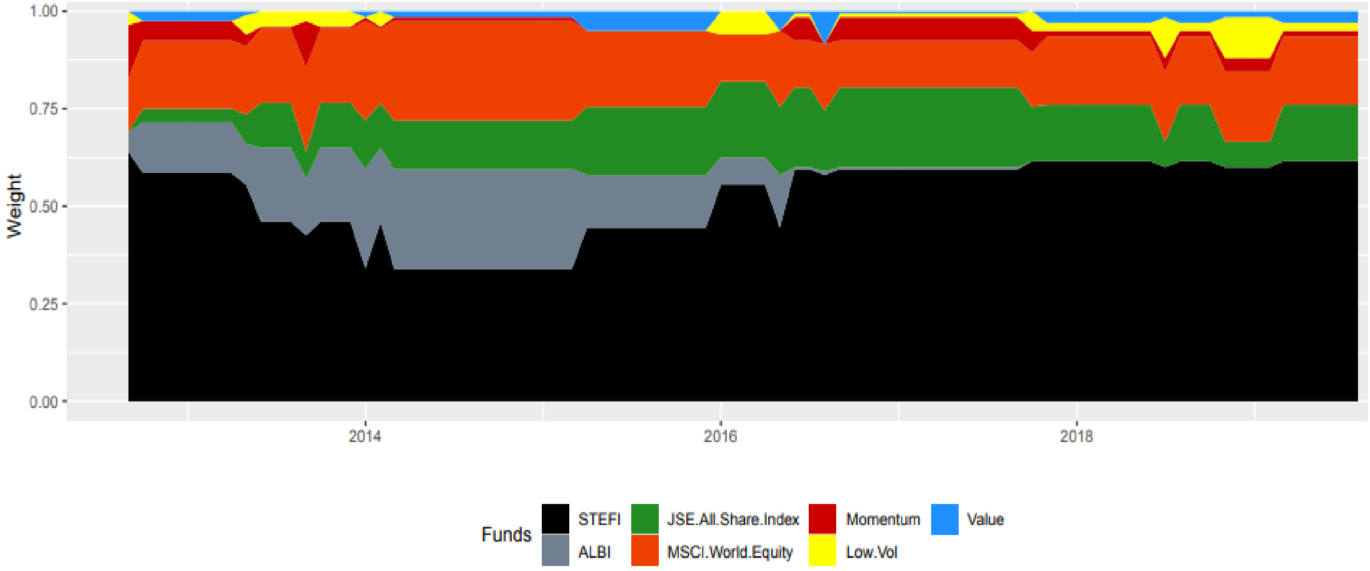
Fund to Shadow		**Fund to Benchmark**	
Alpha (% p.a.)	**-4.04**	Alpha (% p.a.)	0.39
R-Squared	**0.88**	R-Squared	0.97
Correlation	0.94	Correlation	0.98
Tracking Error (% p.a.)	2.66	Tracking Error (% p.a.)	1.61

From the X-RAY results of Stanlib Multi Manager Balanced Fund, we find that the fund fails to outperform the benchmark (SA High Equity UT Sector) on an absolute basis over the period 1 September 2012 – 1 September 2019. Stanlib Multi Manager Balanced Fund also fails to outperforms the benchmark on a risk-adjusted basis as the annualised Sharpe Ratio of the fund is 1.06, compared to the annualised Sharpe Ratio of the SA High Equity UT Sector of 1.24.

Comparing Stanlib Multi Manager Balanced Fund to its shadow fund, which consists out of the following passive asset classes and style indices: **42.5% FTSE/JSE All Share, 27% ALBI, 29% MSCI World Equity, 0% Value, 0% Low Volatility** and **1.5% Momentum**, the fund fails to outperform on an absolute and risk-adjusted basis. A large portion of the variations of returns of Stanlib Multi Manager Balanced Fund can be explained by the holdings of the shadow fund, since the R-squared is 0.88.

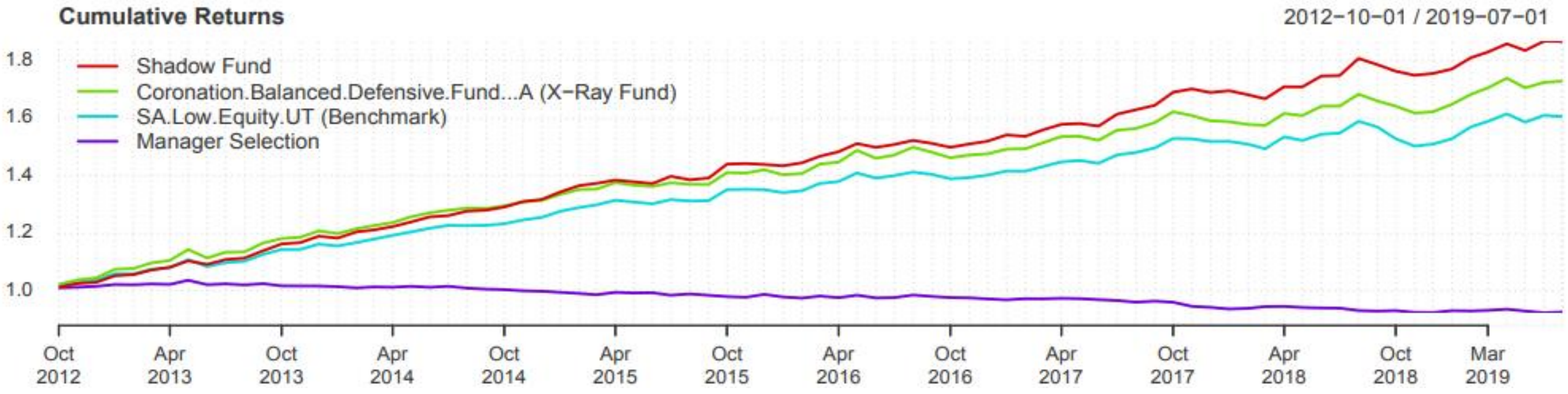
The annualised alpha of Stanlib Multi Manager Balanced Fund versus the shadow fund is -4.04%, which means the fund materially failed to add value over the passive asset classes and style indices it seeks to replicate. Stanlib Multi Manager Balanced Fund, compared to Investec Managed Fund, is less likely to outperform the passive asset classes and style indices it seeks to replicate.

Annexure K: X-RAY Coronation Balanced Defensive Fund



Building Blocks :

Name	Min Weight	Max Weight	Final Weight
ALBI	0	100	0.0
JSE All-Share Index	0	100	14.5
Low Vol	0	100	2.0
Momentum	0	100	1.5
MSCI World Equity	0	100	17.5
STEFI	0	100	61.5
Value	0	100	3.0



Coronation Balanced Defensive Fund X-RAY Results

X-RAY Results of Coronation Balanced Defensive Fund (1 Sep 2012 – 1 Sep 2019)

	Annualised Return (%)	Annualised Std Dev (%)	Annualised Sharpe Ratio
Coronation Balanced Defensive Fund	8.34	4.46	1.87
Shadow Fund	9.57	3.86	2.48
Fund to Benchmark	1.16	1.46	**0.75**
Fund to Shadow	-1.23	1.9	**-0.59**
Benchmark (SA Low Equity UT)	7.18	4.03	1.78
FTSE/JSE All Share (J203T)	10.25	11.2	0.92
MSCI AC World (ZAR TR)	18.92	14.63	1.29
ALBI	7.34	7.56	0.97
STEFI	6.6	0.26	25.66
Momentum	12.89	11.6	1.11
Low Volatility	10.07	9.85	1.02
Value	15.95	12.75	1.25

Summary and Correlations Results of Coronation Balanced Defensive Fund

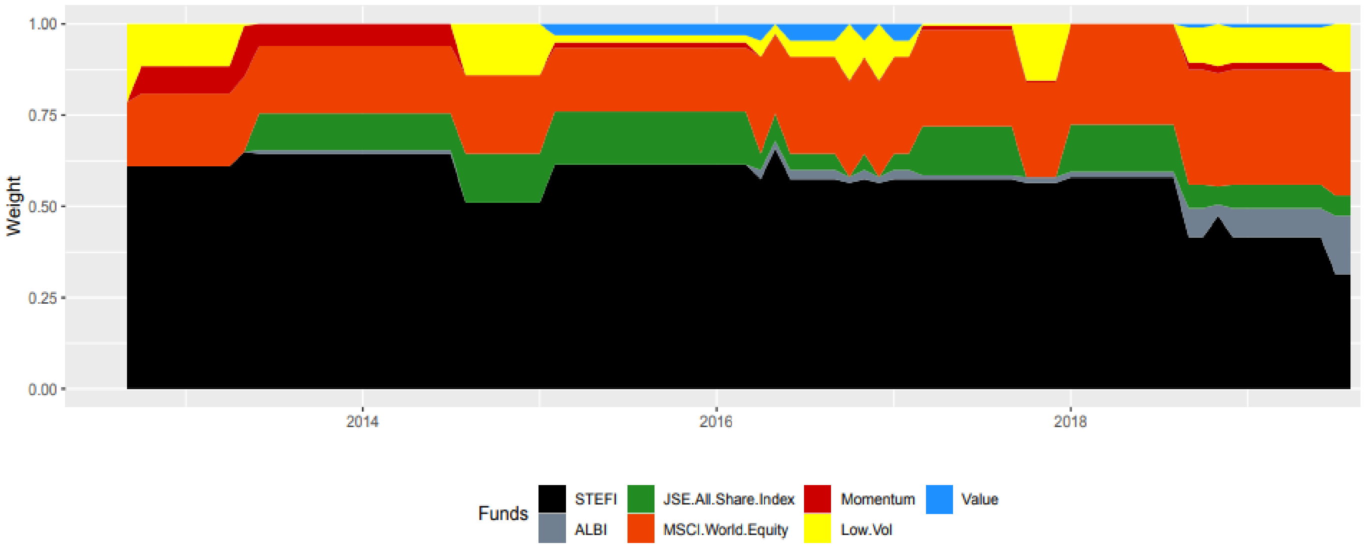
Fund to Shadow		Fund to Benchmark	
Alpha (% p.a.)	**-1.12**	Alpha (% p.a.)	1.59
R-Squared	**0.82**	R-Squared	0.89
Correlation	0.91	Correlation	0.94
Tracking Error (% p.a.)	1.9	Tracking Error (% p.a.)	1.39

From the X-RAY results of Coronation Balanced Defensive Fund, we find that the fund outperforms the benchmark (SA Low Equity UT Sector) on an absolute basis over the period 1 September 2012 – 1 September 2019. Coronation Balanced Defensive Fund also outperforms the benchmark (SA Low Equity UT Sector) on a risk-adjusted basis as the annualised Sharpe Ratio of the fund is 1.87, compared to the annualised Sharpe Ratio of the SA Low Equity UT Sector of 1.78.

Comparing Coronation Balanced Defensive Fund to its shadow fund, which consists out of the following passive asset classes and style indices: **14.5% FTSE/JSE All Share, 61.5% STEFI, 17.5% MSCI World Equity, 3% Value, 2% Low Volatility** and **1.5% Momentum**, the fund fails to outperform on an absolute and risk-adjusted basis. The majority of the variations of returns of Coronation Balanced Defensive Fund can be explained by the holdings of the shadow fund, since the R-squared is 0.82.

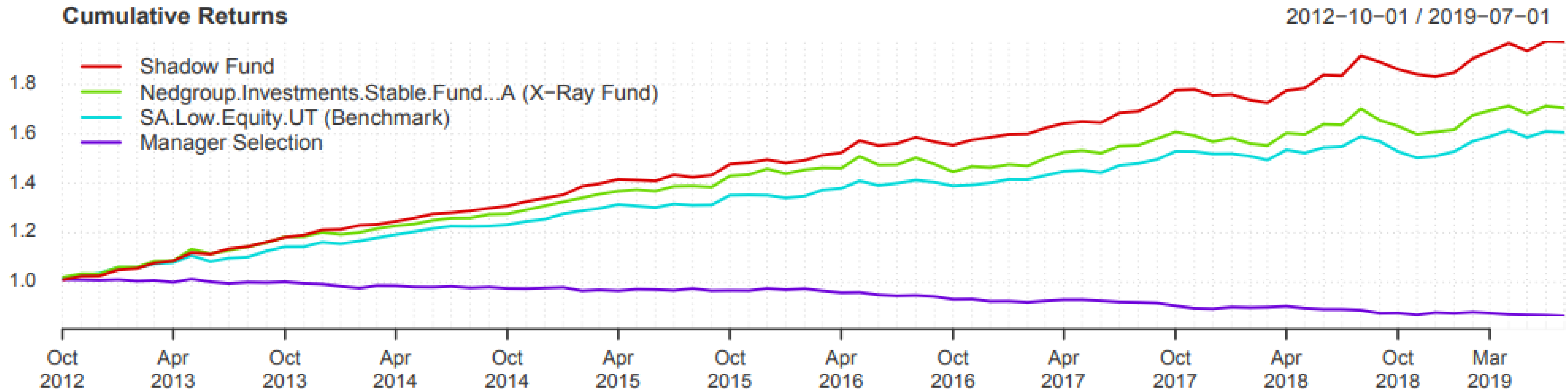
The annualised alpha of Coronation Balanced Defensive Fund versus the shadow fund is -1.12%, which means the fund failed to add value over the passive asset classes and style indices it seeks to replicate.

Annexure L: X-RAY Nedgroup Investments Stable Fund



Building Blocks :

Name	Min Weight	Max Weight	Final Weight
ALBI	0	100	16.0
JSE All-Share Index	0	100	5.5
Low Vol	0	100	13.0
Momentum	0	100	0.0
MSCI World Equity	0	100	34.0
STEFI	0	100	31.5
Value	0	100	0.0



Nedgroup Investments Stable Fund X-RAY Results

X-RAY Results of Nedgroup Investments Stable Fund (1 Sep 2012 – 1 Sep 2019)

	Annualised Return (%)	**Annualised Std Dev (%)**	**Annualised Sharpe Ratio**
Nedgroup Investments Stable Fund	8.11	5.07	1.6
Shadow Fund	10.46	4.35	2.4
Fund to Benchmark	0.93	2.41	**0.37**
Fund to Shadow	-2.35	2.11	**-1.01**
Benchmark (SA Low Equity UT)	7.18	4.03	1.78
FTSE/JSE All Share (J203T)	10.25	11.2	0.92
MSCI AC World (ZAR TR)	18.92	14.63	1.29
ALBI	7.34	7.56	0.97
STEFI	6.6	0.26	25.66
Momentum	12.89	11.6	1.11
Low Volatility	10.07	9.85	1.02
Value	15.95	12.75	1.25

Summary and Correlations Results of Nedgroup Investments Stable Fund

Fund to Shadow		**Fund to Benchmark**	
Alpha (% p.a.)	**-2.13**	Alpha (% p.a.)	1.72
R-Squared	**0.83**	R-Squared	0.74
Correlation	0.91	Correlation	0.86
Tracking Error (% p.a.)	2.11	Tracking Error (% p.a.)	2.38

From the X-RAY results of Nedgroup Investments Stable Fund, we find that the fund outperforms the benchmark (SA Low Equity UT Sector) on an absolute basis over the period 1 September 2012 – 1 September 2019. Nedgroup Investments Stable Fund, however fails also outperforms the benchmark on a risk-adjusted basis as the annualised Sharpe Ratio of the fund is 1.60, compared to the annualised Sharpe Ratio of the SA Low Equity UT Sector of 1.78.

Comparing Nedgroup Investments Stable Fund to its shadow fund, which consists out of the following passive asset classes and style indices: **5.5% FTSE/JSE All Share, 16% ALBI, 31.5% STEFI, 34% MSCI World Equity** and **13% Low Volatility**, the fund fails to outperform on an absolute and risk-adjusted basis. The majority of the variations of returns of Nedgroup Investments Stable Fund can be explained by the holdings of the shadow fund, since the R-squared is 0.83. The annualised alpha of Nedgroup Investments Stable Fund versus the shadow fund is -2.13%, which means the fund materially failed to add value over the passive asset classes and style indices it seeks to replicate.